The impact of RFID-deployments on Out-of-Stocks in various apparel stores

D.S. de Boer

Master thesis

Delft University of Technology

Transport Engineering and Logistics

Delft University of Technology

FACULTY MECHANICAL, MARITIME AND MATERIALS ENGINEERING
Department Marine and Transport Technology

Mekelweg 2
2628 CD Delft
the Netherlands
Phone +31 (0)15-2782889
Fax +31 (0)15-2781397
www.mtt.tudelft.nl

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Initiator (university):	Prof. dr. R.R. Negenborn
Initiator (company):	Drs. S. Merkx
Supervisor (university):	Dr. ir. Y. Pang
Supervisor (company):	I. van der Zanden MSc
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Delft University of Technology

FACULTY OF MECHANICAL, MARITIME AND MATERIALS ENGINEERING
Department of Marine and Transport Technology

Mekelweg 2
2628 CD Delft
the Netherlands
Phone +31 (0)15-2782889
Fax +31 (0)15-2781397
www.mtt.tudelft.nl

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Since the arrival of e-commerce, customer demands have changed. Customers are expecting a high variety of items, which are always available. RFID is gaining a lot of attention in the last years because it enables retailers to increase their inventory accuracy. This should result in an improved replenishment, decreasing the number of out-of-stocks. The problem is that there are different RFID-deployments, which can have diverse influences on various store types.

Your assignment is to compare the different RFID-deployments for various store types regarding the reduction of out-of-stocks. The research should include the magnitude and relevance of the problem, relevant literature, developing and implementing a simulation model, verification and validation of the model and multiple experiments to compare different situations. The research should end with the results, a conclusion and a discussion including recommendations for follow-up research.

The report should comply with the guidelines of the section. Details can be found on the website.

The professor,

Dr. ir. Y. Pang

Preface

This research was conducted as final part of my Master program Transportation Engineering and Logistics at the faculty of Mechanical Engineering of Delft University of Technology. In this report, I present my research on the impact of RFID-deployments on out-of-stocks in various apparel stores. It should give readers an insight into how apparel stores work, the current literature about RFID based replenishment the benefits of RFID in apparel stores and presents a model which can be used to test the influence of various parameters on the reduction of out-of-stocks.

I would like to thank Joseph Owusu and Sander Merkx for giving me the opportunity to do my graduation assignment at Mieloo & Alexander. Furthermore, I would like to thank Ivo van der Zanden for being my day-to-day supervisor at Mieloo & Alexander. He helped me with forming, improving and finalising my research with feedback sessions and support. During the research, I had several meeting at the university with Rudy Negenborn as initiator and Yusong Pang as my daily supervisor. The sessions helped me define my scope, pay attention to the academic relevance and gave me new insights. I would like to thank both of them for all their feedback during this research and prior research I performed with their help.

Last, but definitely not least, I would like to thank my parents for their support the last 25 years, without them, I would not have been where I am right now. Furthermore, I would like to thank all my friends for their help and support over the past 7.5 years at the Delft University of Technology, especially for the time we spend outside of the university.

Daan de Boer
Den Haag, the Netherlands
December 22, 2017

Summary

The retail market is changing rapidly. Many new offline, as well as online competitors, arrived. As a result, customers became more demanding. One of the critical elements is that customers expect a high variety of products that are always available. Out of Stocks (OoSs) in apparel stores result in lost sales in the short term and a declining brand reputation in the long run. For many retailers, it is therefore critical to minimise their OoSs. A high inventory accuracy is necessary to reduce the number of OoSs. This is practically unable to achieve with traditional techniques. Radio Frequency IDentification (RFID) has the potential to increase the inventory accuracy, thereby reducing the number of OoSs. RFIDs in the apparel retail, especially more sophisticated deployments are relatively new and specific benefits for various store types are unknown. This research compares different RFID-deployments for apparel stores regarding the reduction of OoSs.

An apparel store exists out of a backroom and a sales floor. Both can be seen as inventory systems, which have to be replenished to prevent OoSs. To achieve this, retail stores use replenishment systems, based on the recorded inventory. The problem in retail stores is that there are inventory losses, mainly due to internal and external theft, which are not registered. The result is an increasing discrepancy between the actual and recorded inventory. As a result, items that appear to be available in the inventory system are not. An effect is an increasing number of OoSs. Apparel stores with barcode scanners correct the inventory with an inventory count. During an inventory count, the recorded inventory is set equal to the actual inventory. It is only executed once or twice a year since it is a labour intensive process. RFID enables inventory counts to be performed more frequently. The following RFID-deployments are compared in this research: handheld readers, a robot reader, a combination of overhead and handheld readers and overhead readers. The deployments are linked to inventory counts that are performed once every seven days, once a day, partly continuous and continuous inventory counts. All deployments for various store types are compared to the original situation. To be able to analyse the different situations, a base model is constructed. The base model is implemented in a discrete event simulation model in which several parameters can be adjusted. The Key Performance Indicator (KPI) to measure the performance is the OoS percentage. The following parameters are adjusted in the experiments to mimic various store types: 1) the ratio between the sales floor and backroom, 2) the average number of items per Stock

Keeping Unit (SKU), 3) the replenishment frequency. RFID significantly reduces the OoSs compared to the original store for each store configuration. The average reduction of OoSs for the base model is 49%. The results for different ratios between the sales floor and backroom hardly differ. The reduction of OoSs in stores with a high quantity of items per SKU is on average 70%, compared to 31% with low quantities. Changing the replenishment frequency showed similar results. The average reduction of the most frequent replenished stores was 66% and for the less frequent replenished stores 39%. To test if the deployments are viable, the reduction of OoSs is linked to the increase in sales. This increase is compared to the increase in average inventory. For each situation, the percentage increase in sales is higher than the increase in inventory; each deployment is therefore viable.

It can be concluded that for each store configuration, RFID significantly reduces the number of OoSs. The implementations hardly differ from each other for a particular store configuration. Regarding the results of this research, it does not matter which RFID-deployment is implemented. From the sensitivity analysis can be concluded that other factors as the inventory losses, inventory turnover rate and replenishment threshold values significantly influence the number of OoSs. The research is limited because model simplifications are made, different elements of the cost-benefit analysis are left out, and real data from a store is not used. Follow up research into one of these three fields is recommended.

Samenvatting

De retailmarkt verandert in een hoog tempo. Afgelopen tijd is er veel concurrentie bijgekomen, zowel offline als online. Het gevolg is dat klanten in het algemeen steeds meer eisend zijn geworden. Dit uit zich in klanten die een grote verscheidenheid aan producten verwachten welke altijd beschikbaar zijn. Out-of-stocks in kledingwinkels resulteren in gemiste verkopen op de korte termijn en een afnemende reputatie op de lange termijn. Voor veel retailers is het daarom van cruciaal belang om hun OoSs te minimaliseren. Een hoge voorraadnauwkeurigheid is nodig om het aantal OoSs te verminderen. Dit is praktisch gezien onmogelijk om te bereiken met traditionele technieken. RFID heeft het potentieel om de nauwkeurigheid van de voorraad te verhogen, waardoor het aantal OoSs verminderd kan worden. RFID in kledingwinkels is relatief nieuw, voornamelijk de meer geavanceerde implementaties. Specifieke voordelen van de verschillende implementaties voor verschillende winkeltypes zijn vaak onbekend. Dit onderzoek vergelijkt de invloed van verschillende RFID-implementaties op het reduceren van out-of-stocks voor verschillende winkeltypes.

Een kledingwinkel bestaat uit een backroom en een verkoopvloer. Beide kunnen als voorraadsystemen gezien worden, die bijgevuld moeten worden om OoSs te voorkomen. Om de voorraden bij te vullen gebruiken winkels bevoorradingssysteem, gebaseerd op de geregistreerde voorraad. Het probleem is dat er in de praktijk voorraadverliezen zijn in winkels, voornamelijk veroorzaakt door interne en externe diefstal, die niet worden geregistreerd. Het resultaat is een toenemend verschil tussen de werkelijke en geregistreerde voorraad. Als gevolg van dit verschil lijken producten beschikbaar, terwijl ze dat in werkelijkheid niet zijn. Het effect is een toename in het aantal OoSs. Traditionele kledingwinkels met barcode scanners corrigeren de voorraad met een periodieke telling. Tijdens een telling wordt de geregistreerde voorraad gelijkgesteld aan de werkelijke voorraad. Aangezien het een arbeidsintensief proces is, wordt het maar een of twee keer per jaar uitgevoerd. RFID maakt het mogelijk om de voorraad vaker te tellen. De volgende RFID-implementaties zijn vergeleken in dit onderzoek: handheld readers, een robot reader, een combinatie van overhead en handheld readers en alleen maar overhead readers. De implementaties zijn gekoppeld aan een telling van de voorraad eens per 7 dagen, eens per dag, gedeeltelijk continu en volledig continu. De implementaties voor verschillende winkeltypen worden vergeleken met de oorspronkelijke situatie. Om de verschillende situaties te analyseren is een basis model geconstrueerd. Het basis

model is geïmplementeerd in een discreet event simulatiemodel, waarin verschillende parameters aangepast kunnen worden. De KPI om de prestaties te meten is het OoS-percentage. De volgende parameters worden aangepast in de experimenten om verschillende soorten winkels na te bootsen: 1) de verhouding tussen de verkoopvloer en de backroom, 2) het gemiddelde aantal artikelen per SKU, 3) de bevoorradingsfrequentie. RFID reduceert het aantal OoSs in elke winkel configuratie aanzienlijk in vergelijking met de oorspronkelijke winkel. De gemiddelde reductie van OoS voor het basismodel is 49%. De resultaten voor de verhoudingen tussen de verkoopvloer en de backroom verschillen nauwelijks. De reductie van OoSs in winkels met een grotere hoeveelheid artikelen per SKU is gemiddeld 70%, vergeleken met 31% voor lage hoeveelheden. Het veranderen van de bevoorradingsfrequentie vertoont vergelijkbare resultaten. De gemiddelde reductie van de meest frequent aangevulde winkel is 66% en voor minder frequent bijgevulde winkels 39%. Om te testen of de implementaties reëel zijn, is de reductie van het aantal OoSs gekoppeld aan de toename van de verkopen. Deze toename wordt vergeleken met de toename van de gemiddelde voorraad. Voor elke situatie is de percentuele toename van verkochte producten hoger dan de percentuele toename van de voorraad; elke implementatie is daarom realistisch.

Er kan worden geconcludeerd dat voor elke winkel configuratie RFID het aantal OoSS aanzienlijk is gereduceerd. De implementaties onderling verschillen nauwelijks van elkaar voor elke winkel configuratie. Naar aanleiding van de resultaten van dit onderzoek maakt het niet uit welke RFID-implementatie wordt geïmplementeerd. Uit de gevoeligheidsanalyse kan worden geconcludeerd dat andere factoren zoals de voorraadverliezen, de omloopsnelheid van de voorraad en de drempelwaarden voor bestellingen een aanzienlijke invloed hebben op het OoS percentage. Het onderzoek is beperkt op bepaalde vlakken: vereenvoudigingen waren nodig om het model te maken, verschillende elementen van de kosten-batenanalyse zijn weggelaten en er is geen echte data van bestaande winkels gebruikt. De toevoeging van een van deze onderdelen wordt aangeraden als vervolgonderzoek.

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Glossary

List of Acronyms

AI	Artificial Intelligence
Auto ID	Automatic Identification
AQ	Actual Quantity
DC	Distribution Centre
EAN	European Article Numbering
EAS	Electronic Article Surveillance
EPC	Electronic Product Code
FMCG	Fast Moving Consumer Good
IRA	Inventory Record Accuracy
IRI	Inventory Record Inaccuracy
KPI	Key Performance Indicator
MA	Mieloo & Alexander
OoS	Out of Stock
POS	Point Of Sale
RFID	Radio Frequency IDentification
ROI	Return On Investment
RQ	Record Quantity
SKU	Stock Keeping Unit
TU Delft	Delft University of Technology

UPC Universal Product Code

US United States

List of Symbols

Abbreviations

λ	Inter-arrival time between customers
σ	Standard deviation
a,b	Lower and upper limit of a distribution
a_k	The quantity of items received at period k
D	Customer demand
d	Average customer demand
E_d	Percentage of delivery errors
e_k	The quantity of the items sold at period k
f	Calculation factor for the average inventory
I_i^k	Inventory for SKU i
I_{k+1}	The number of items in the beginning of the next period
$I_{k,br}$	Inventory in the backroom at period k
$I_{k,sf}$	Inventory on the sales floor at period k
$I_{k,t}$	Total inventory at period k
I_k	Inventory at period k
I_l	Actual inventory losses %
I_t	The total inventory
i_t	Inventory turnover
l	Inventory losses, % of demand
l_k	Inventory losses at period k
M_R	Rounding method for determining threshold values
n	Number of runs
N_c	Number of customers a year
N_{lost}	Number of lost items
N_{sales}	Number of sold items
N_{SKUs}	Number of SKUs
Q_i^a	Actual quantity of SKU i
Q_i^r	Recorded quantity of SKU i
q_{SKU}	Average quantity per SKU
R	Review period
R_1	Frequency of review period for in-store replenishment

R_2	Frequency of review period for to-store replenishment
R_3	Frequency of inventory counts
R_a	Inventory record accuracy
R_i	Inventory record inaccuracy
$r_{sf/br}$	Sales floor/backroom ratio
S	Order up to value for replenishment
s	Threshold value for replenishment
s_{sf}	Threshold value for sales floor replenishment
s_t	Threshold value for store replenishment
T_0	Initialisation time
t_{end}	Total simulation time
T_E	Data-collection time
t_{lead}	Lead time
t_{sim}	Current simulation time
w	Width of the confidence interval
$z_{\alpha/2}$	Critical value of the confidence interval

Chapter 1

Introduction

Recent years have been disruptive for retail and chain stores. Since 2011 more than 2800 retail and chain stores went bankrupt in the Netherlands. The 25 biggest bankruptcies together are accounted for more than 33.000 layoffs [Consultancy.nl, 2016]. The largest and one of the most recent ones is V&D, where more than 10.000 jobs disappeared [AD, 2016]. Other retail chains are closing stores at a rapid rate to prevent bankruptcy. For example Blokker Holding, which is selling off all of its retail chains except for Blokker itself. Resulting in a loss of 1.900 jobs and a reduction of the concerns 3.000 stores in 2010 to 400 in the near future [der Heijden, 2017].

This trend can be seen all over Europe and the United States, where retailers are struggling to keep up with the substantial changes in the retail landscape. The most disruptive changes are the rise of e-commerce, new retail concepts such as the Action, Zara, Zalando, H&M and the rise of mass merchandisers and superstores such as Wal-Mart and Carrefour. Simultaneously, retailers see an increase in the diversity of customer groups due to the ageing of populations, increase in wealth, changing life patterns, and other long-term trends [Gagnon and Chu, 2005].

These changes have resulted in customers that are not only more demanding and price-conscious than ever before, their behaviour has become increasingly difficult to predict [Thiesse and Buckel, 2015]. Due to the firm competition and customers being less brand loyal, retailers should come up with ideas to improve their turnover, customer satisfaction and product margins. These ideas can vary from improving product availability, marketing, product innovation and the supply chain, to shipping from the store, new replenishment models, increased customer service, magic mirrors or buy online pickup in store. However, the bottom line is that retailers can not sell items that are unavailable. Retailers should have at least a high mix of decently priced products which are always available. To assure the availability of items, retailers often use automated replenishment systems. Replenishment systems are dependent on the recorded inventory. For a replenishment system to function correctly, a high inventory record accuracy is necessary. However, a high level of accuracy is often lacking in the retail industry and is not realistic to obtain with traditional manual counting and bar-codes, due to the costs of human labour and their error sensitivity [Kök and Shang, 2007]. Hence, another method to obtain more frequent and accurate information to increase the inventory accuracy is necessary.

Many retailers are currently looking into the implementation of improved Automatic Identification (Auto ID) technologies, such as Radio Frequency IDentification (RFID), in their retail stores to achieve a higher inventory accuracy. Thereby, enabling more accurate replenishment. RFID has been gaining more and more attention in recent years since the technology has matured and is becoming increasingly affordable.

Mieloo & Alexander

This research is performed as part of the Master Transport Engineering and Logistics, at the Delft University of Technology (TU Delft). It is set up in combination with Mieloo & Alexander and is focused on apparel retailers. In this section, a short introduction is given about Mieloo & Alexander and their relevance to RFID in the apparel retail industry. A more comprehensive explanation is in Appendix B-1.

"Mieloo & Alexander Business Integrators is specialised in delivering "technology-enabled supply chain improvement" [M&A,]. One of their focus area's is designing custom solutions with Auto ID technologies, mainly RFID. One of the industries Mieloo & Alexander (MA) is currently deploying RFID solutions in, is the apparel retail sector. The apparel retail sector is increasingly acknowledging the benefits of RFID-deployments, especially regarding item-level tagging. A comprehensive comparison with multiple RFID-deployments for different types of retail stores is currently unavailable. The majority of information about the benefits of RFID solutions is given in advertising leaflets and white papers from companies that sell RFID technologies or is fundamental research with one fast moving consumer product in a single inventory system.

It is therefore hard for M&A to specify specific benefits of between various aspects of the different RFID-deployments for various apparel stores. This research is set up to provide an insight into the benefits of different RFID implementations for apparel stores configurations, regarding the improvement of item availability.

1-1 Problem statement

Traditional apparel retailers are in heavy weather, due to high competition. This competition results in retailers having to sell at least a high mix variety of items against low margins [Al-Kassab et al., 2009]. In order to survive or improve their competitive position, retailers have to sell more items or increase the margins on items [ChainLink, 2014]. Multiple reasons can be pointed out for the lack of sales or low margins. For example, the marketing strategy is not striking enough, customers do not like the product lines and designs, the brand has a wrong image or the store layout is not optimal. In this research is assumed that retailers sell items that customers want, otherwise, they would not exist. Hence, critical for selling items is, that they have to be available in store on the sales floor. A frequent occurring phenomenon with apparel retailers is the lack of item availability due to the high variety of models, sizes and colours and incorrect inventory record. The lack of availability results in lost sales in the short term and a negative impact on the brand reputation in the long term [Trautrims et al., 2009]. In order to survive the competition, product availability is of high importance [Spielmaker, 2012]. If an item is unavailable, it is called Out of Stock (OoS). In order to assure on-floor availability, replenishment systems based on the recorded inventory are used. The problem, in reality, is that it is often unknown for retailers what is exactly available inside their stores. The reason behind this is that errors are made and shrinkage, mainly theft, occurs throughout the retail store and that there is a lack of information to compensate these errors [DeHoratius et al., 2008]. The result over time is a growing discrepancy between the actual inventory and the recorded inventory. Resulting in a replenishment system based on incorrect information, resulting in more OoSs [Kang and Gershwin, 2005].

Not only the replenishment is affected by the lack of information. The lack of information withholds retailers from implementing numerous improvements. Therefore, retailers are looking to improve the collecting of information. Barcodes already improved collecting information significantly, but barcodes have many drawbacks. Retailers are therefore looking into other possibilities to collect information with the use of Auto ID.

RFID is one of the most promising technologies for Auto ID in the retail sector [Nayak et al., 2015]. The deployments of RFID can vary from a single handheld reader in order scan items periodically by hand to a fully integrated overhead system that automatically scans the whole store continuously. RFID enables the possibility to obtain information about the inventory much faster, often resulting in a more frequent inventory count [Bertolini et al., 2012]. As a result, the discrepancy between the actual inventory and recorded inventory decreases and thus the inventory accuracy increases. The various implementations result in different levels of information. The problem is that it is unclear to what extent each RFID-deployment will help to reduce the number of OoSs for different retail stores.

A lot of research is done on various aspects of the retail processes and the improvement of retail replenishment. Studies into the benefits of RFID in retail stores in general, as well as studies into RFID as an enabler of specific process improvements, are done ([Wong and McFarlane, 2007], [Thiesse et al., 2007]). Specific studies that study the influence of extra information on the replenishment of one Fast Moving Consumer Good (FMCG) in a single inventory system to reduce the OoSs are also performed [Kang, 2004]. However, there is a research gap between fundamental research and a comprehensive analysis of a RFID-pilot for a specific store. The fact that RFID can help to reduce the number of OoSs is already proven in several studies. To what extent different RFID-deployments reduce the number of OoSs for different store configurations is unclear.

1-2 Research objective

The main objective is comparing the influence of information obtained by different RFID-deployments for various store configurations regarding the reduction of OoSs. This makes it possible to give a more detailed advice about the benefits of implementing a specific RFID-deployment for a specific type of retail store, without running a lengthy and costly pilot project. In order to achieve this objective, the following main and sub-questions are answered throughout this report.

The main research question is:

To what extent does more information, obtained by different RFID-deployments, result in less out-of-stocks for various apparel store configurations?

The sub-questions are:

2. *How is the apparel retail sector transformed up to today and why is this research relevant nowadays?*

3. *What elements of RFID based replenishment in retail stores are discussed in the literature?*

4. *What is the current problem in retail stores, what is more information and how can it be used to solve the problems?*

5. *What are the different RFID-deployments and to what extent can they obtain more information?*

6. *What are the different types of apparel store configurations?*

7. *How can the different RFID-deployments be compared for different store configurations?*

8. *To what extent do the RFID-deployments reduce the number of OoSs for the different experiments?*

The questions are answered throughout the report. Each question number corresponds with a chapter in which the sub-question is answered. The sub-question is restated in the introduction of each chapter and is answered in the conclusion. In the end of the report, the conclusion summarises all the answers and gives a general conclusion.

1-3 Approach

The different RFID-deployments are compared with the use of a discrete event simulation made in Python. The simulation model enables testing the different RFID-deployments for various store configurations in one model, within limited time and without setting up several expensive pilot stores. Before running the simulations, a base model is constructed. In order to construct the model, the first part of the report contains the market analysis, a literature review, the system and problem analysis and a comparison between the different RFID-deployments, in which the relevant aspects are discussed. Where after the base model is created to compare the RFID-deployments. The second part explains how the model is created, what experiments are performed and presents the results of the experiments. The third part contains the discussion and conclusion.

1-4 Structure of the report

This report is structured as follows: in Chapter 2, background information is given about the history of retailing, the basics of retailing including the ongoing transition from single-channel to omni-channel retailing, the basics of Auto ID and argumentation for the focus on replenishment models is give. Chapter 3 presents information about current studies into RFID-enabled retail replenishment models and the relevance of the research. In Chapter 4, a comprehensive analysis of a retail store and the research problem is made. Chapter 5 discusses the RFID-deployments. In Chapter 6 a base model is constructed in order to compare the different RFID-deployments for various store configurations. The implementation of this model into a simulation model, including the implementation of the RFID-deployments is discussed in Chapter 7. Chapter 8 presents the experimental plan, including calibration, verification, validation and the experimental results of the model. In Chapter 9 is the conclusion of the research is presented and the research is discussed, including the research limitations, recommendations for further research and a general overview of the possible future of apparel retailing. The scientific paper and additional information can be found in the Appendices A-1 to B-4.

Chapter 2

Market analysis

To understand the problem in apparel retail stores, background information is necessary about relevant aspects and the continuously changing world, including changes in the apparel retail sector, data capturing technologies and the relevance for retailers.

This chapter answers the following research question:

How is the apparel retail sector transformed up to today and why is this research relevant nowadays?

The chapter presents background information about retail in general, the newest trends in the apparel retail sector and data capturing technologies. Furthermore, it introduces the basics of Radio Frequency IDentification (RFID) in the apparel retail sector and the reasons for retailers to adopt RFID to improve the replenishment process.

2-1 The history of retailing

Retailing has drastically changed in the past century. Before the beginning of the last century, it was very common for people to sew their own clothes or buy their clothes around the corner in mom-and-pop shops. The first decades of the past century marked the transition from mom-and-pop shops and general stores to department stores. Department stores and retail chains started to grow and became very common. The first significant changes in the retail process itself came in the second part of the last century. The first electronic cash register was invented, and Big Box retailers started to arrive with the opening of the first Wal-Mart. About 40 years ago, bar codes were introduced in retailing, which enabled automatic identification and vastly improved the methods for inventory counting and checking out at the cash register. These improvements were all in traditional mortar-and-brick retail stores. Other essential steps in the history of retail are the combination of television and shopping in the first season of 'The Home Shopping Network', the first book sold by Amazon online, the dawn of social media: including business pages on Facebook and the comeback of main street shopping [Braun, 2015].

Rise of online competition
Apparel retail notably changed in the last two decades due to the rise of e-commerce and ongoing digitalisation. New online retailers started to arise which became very dominant. They can be considered a disruptive development. Many traditional retailers started online stores, besides their offline stores, to counter these developments, resulting in the question for online players whether they should be present offline as well [Verhoef et al., 2015]. Where the customers first had the choice between a few stores in his city, they now have the choice between many offline stores and even more online stores. This competition highly raised the standards for quality, prices, a variety of products and sizes, service, and up-to-date fashion, which resulted in highly dynamical processes with extensive supply chains. The up-to-date fashion requirements resulted in goods almost being 'perishable'. Where a trend could last a decade about 100 years ago, a year now has multiple trends. The high standard of a variety of products, sizes and service arrived from the online retailers, where products are always available. Other advantages of online retailing are that the customer does not have to wait for an employee to see if their size is still available or in a queue for a checkout point and that he can compare prices. However, offline stores also have their advantages such as personal contact, gaining inspiring new ideas from walking through the store, feeling the fabric and quality, seeing the colour in real life and the fact that customers do not have to wait until their bought item is delivered. The majority of purchases are therefore still bought in offline stores. It is expected that the retail market share of e-commerce in the Netherlands in 2017 only accounts for 9.5% [Retail.research, 2017].

All these competitive factors, in combination with the financial crises, have resulted in profit falls for large numbers of retailers. Even the retailers who adopted online strategies besides their offline activities, can not always withstand the competition. Some retailers have specialised in a particular market segment to survive. Others have to improve processes or have to come up with new ideas to survive. One of the ideas is omni-channel retailing. However, before the concept of omni-channel retailing is clarified the basics of retailing are explained.

2-2 Basics of retailing

Retailing is defined as: 'Commercial transaction in which a buyer intends to consume the goods or service through personal, family or household use' [Dictionary,]. A retailer is defined as: 'A business or person that sells goods to the consumer, as opposed to a wholesaler or supplier, who normally sell their goods to another business' [Dictionary,]. To sell goods, the retailer has to acquire these goods through a supply chain network. A straightforward retail supply chain is shown in Figure 2-1. The material flow is presented by arrows and goes from left to right, although not shown in the figure, there are situations where material flows the other way around. For example defect or wrong products. The suppliers supply raw materials to the manufacturer, the manufacturer produces goods from these raw materials. Distributors buy these goods, often in large quantities. Distributors distribute these goods to different retailers, or the retailers buy their goods from these distributors. The customer buys goods from the retailer, which can be an offline or an online retailer. A typical supply chain for a retailer has many of these entities. A retailer like Wal-Mart sells, for example, thousands of products from thousands of suppliers [Sikander, 2005].

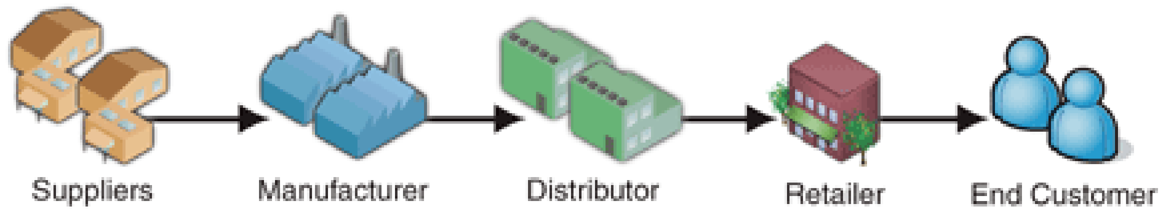

Figure 2-1: A simple retail supply chain - source: Microsoft

2-2-1 From single to omni-channel retailing

Traditional brick and mortar stores and retail chains are single-channel retailers. Single-channel retailing represents a retailer that sells its products only through a single platform. For example only brick-and-mortar stores. In the beginning of retailing, there were only single-channel retailers. Later on, some of the retailers started selling their products through sales catalogues or the television. These were the first multi-channel retailers. The number of multi-channel retailers stayed relatively low until the rise of e-commerce.

Emergence of multi-channel strategies
The rise of e-commerce was a disruptive development in retailing, especially in specific retail markets. Many new online retailers arose. To counter these competitors, many retailers have initiated multi-channel strategies [Verhoef et al., 2015]. The question first arose to mortar-and-brick retailers if they should add a website. However, it also appeared to online retailers, who faced the question of whether they should be present offline as well [Avery et al., 2012]. In the end, many new multi-channel retailers originated.

The current status
The problem with multi-channel retailing is the lack of integration between the channels. The attention was mostly focused on the growth of the online channels. These were often developed and managed as separate firms [Verhoef, 2012]. Most of the times, the only integration were similar assortments and prices across the channels.

The existence of both online channels and offline channels resulted in customers who were more demanding. They want to touch, see, feel and try on merchandise and at the same time required a high variety of products, low prices and extra content such as the possibility to view product reviews and ratings. To keep these customers, retailers have to evolve. Some specialised in a specific market, but most are trying to renew their brand and improve their processes and services. Part of the transformation is improving the traditional processes in-store, and another part is integrating all the different channels. Eventually, the goal for most retailers is to evolve into a seamless "omni-channel retailing" experience, existing out of improved and integrated processes.

2-2-2 Omni-channel retailing

Omni-channel retailing is often referred to as a seamless retail world where customers can shop across channels, anywhere and at any time with a standardised high level of service.

In [Beck and Rygl, 2015] the category omni-channel retailers is defined as follows:
The retailer offers the customer all channels that are currently widespread, which at present means the physical store, catalogue, telephone, online shop and mobile shop. Additionally, the customer can trigger full interaction and/or the retailer controls full integration of all channels.

The research divides omni-channel retailing into two categories. The first category is from the customer point of view, where all channels interact fully from the customer's viewpoint. For example, if customers can return merchandise regardless of where they bought it. The second category applies if the channels are fully integrated from the retailer's point of view. For example, if the retailer shares customer information, pricing, and inventory data across all channels. In papers is often spoken about the customer being central. However, in practice, both categories are often be combined.

The three different strategies of retailing are schematically represented in Figure 2-2.

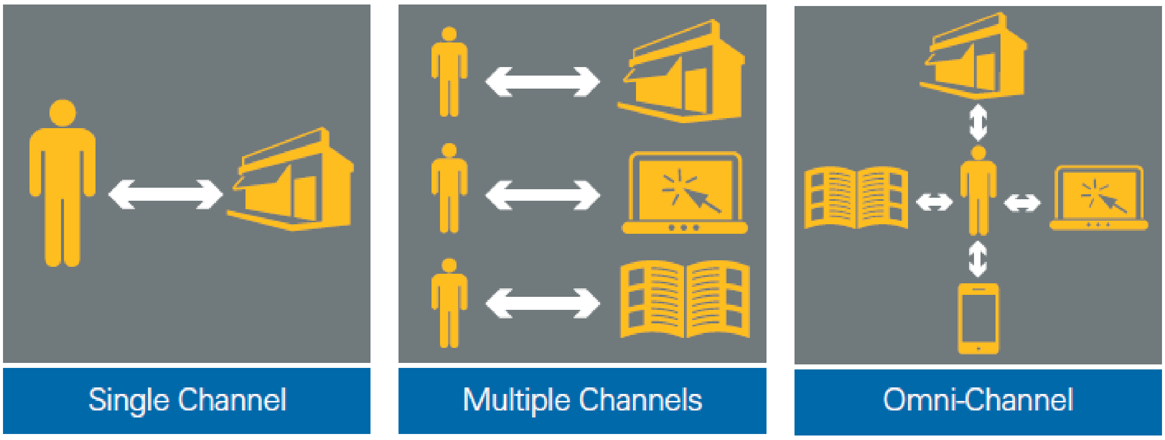

Figure 2-2: Different retailing strategies - source: Tyco Retail Solutions

Seamless integration
In omni-channel retailing, there is a seamless integration between all the different channels. In practice, the primary integration is between online platforms such as a website or an app and offline retail stores. A practical example from the customer point of view is that the integration could mean looking for an item online, checking the availability of that item in a local retail store online, buying it directly and picking it up in-store one hour later. Alternatively, visa versa, seeing an item in a store and ordering it, or ordering another colour of the same model which is currently unavailable, directly in-store. It is then sent to your home. In both situations, the customer expects the same level of service, prices and conditions offline as well as online. A practical example from the retailer point of view is also a seamless integration between different channels. However, this integration then accounts for the supply chains or the inventory. For example, if an online retailer can send an item to a customer directly from a local store instead of a distribution centre, it means that it could lower its total inventory, send items faster to the customers and is more energy efficient. The key element is transforming the shopping experience through integration. Although this trend starts occurring in more sectors, most developments are happening in the apparel retail sector.

Prior improvements with RFID
The full integration and a completed transformation to omni-channel retailing are still far away for retailers. However, retailers are more and more thinking about improving specific processes in their retail store to start the transition. These improvements can, for example, be the practical examples named above or reducing the Out of Stock (OoS) situations, reducing shrinkage and identifying and finding items much quicker in-store. The similarity between implementing omni-channel retailing and implementing process improvements is the requirement of a high level of inventory accuracy. The problem retailers have however is the lack of inventory accuracy. An average inventory accuracy among apparel retailers is about 67.4% [Salmon, 2016]. Chapter 4 analyses the origin of this problem comprehensively. The main reason is a combination of errors made and a lack of accurate information throughout the retail process. To implement specific process improvements as part of the transition to omni-channel retailing, more information has to be obtained in the retail process in order to increase the inventory accuracy. The only practical way to obtain enough information is with the use of Automatic Identification (Auto ID). Within Auto ID technologies, RFID is the most promising for the apparel retail industry. RFID will enable tasks to be less labour-intensive all the way to fully automated tasks such as automated inventory counting. The next chapter explains the basics of inventory identification with the use of Auto ID and RFID.

2-3 Automatic identification of products

To be able to keep track of the inventory, it must be able to identify the products. In the early days of retailing, most of the retailers owned their retail store and had a limited collection. They were able to keep up with the inventory by writing everything down. Simultaneously, they did not have to worry about integration between offline and online stores. As stores became larger, tracking and identifying inventory became a labour-intensive task and stalled other processes. In 1974 the first barcodes were used at Marsh's supermarket in Troy, Ohio. The barcodes were used to automate the scanning of items at the check-out register [Rosistem,]. After this implementation, barcodes became the standard in the retail industry and were also used to count the inventory. However, barcodes have several drawbacks. For example, the data that it contains is limited, it is not possible to scan multiple simultaneously, it needs a line of sight to be scanned, and they are not unique. Therefore, a majority of the retailers are currently looking into RFID to replace barcodes. This section discusses what barcodes are, what RFID is, how it works and what the differences are.

2-3-1 Barcodes

The idea of automated identification to enable an automated checkout system in the retail was already around for a while. However, it took the industry until 1973 to come up with a Universal Product Code (UPC). This happened shortly after the first barcode scanner was installed at Marsh's supermarket and the first product, a pack of chewing gum, was scanned [GS1,]. In 1977, an extra number was added to the UPC resulting in a barcode of 13 numbers. This extension allowed it to be used outside of the United States (US). Simultaneously, the European Article Numbering (EAN) was formed. Since then, the EAN started taking over the world. In the following years, many different types and standards for barcodes started to arise. The first generation of barcodes is one dimensional and consists out of lines and spaces. A newer type of barcode is a two-dimensional barcode, also called a matrix code. Such a code can represent more data per unit area.

Examples of barcodes
The figures below are used to give an understanding of the anatomy of a UPC barcode and a Electronic Product Code (EPC) and shows the amount of data one- and two-dimensional barcodes can contain per surface area. Figure 2-3 shows the anatomy of a standard UPC barcode. The main elements are a manufacturer code and a product code. In Figure 2-4 an EPC is shown, which can contain a lot more data including a unique object identification code for each item. The advantage of an EPC is that the item is unique. Hence, the item-history is traceable, it can be exactly known which items are in-store and characteristics can be added to particular items, such as if it is sold and where it is bought. The reason for the development of two dimensional data matrices can be visualised with Figures 2-5, 2-6, 2-7 and 2-8. The first two represent the UPC of Figure 2-3. Both can be presented in a relatively small area. However, the reason for the use of data matrices becomes clear when the EPC of Figure 2-4 has to be presented in a barcode. However, the downside of two-dimensional barcodes is that it takes longer for a scanner to read them, that is why supermarkets still use one-dimensional barcodes [Darman, 2015]. Simultaneously, the other drawbacks of barcodes subsist. The main drawback of the visual identification codes is that each item has to be scanned individually.

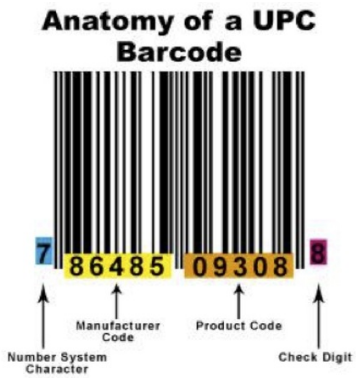

Figure 2-3: The anatomy of a barcode - source: A barcode business

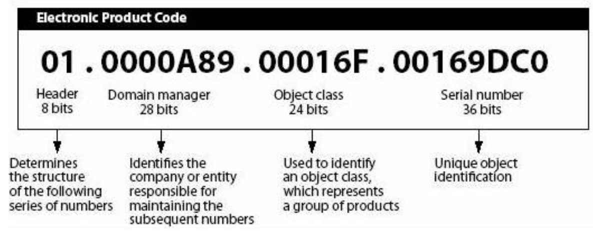

Figure 2-4: The anatomy of an EPC - source: Forrester Research, Inc

786485093088

Figure 2-5: The UPC in a regular barcode - source: TEC-IT

Figure 2-6: The same UPC code in a 2D data matrix - source: TEC-IT

01.0000A89.00016F.00169DC0

Figure 2-7: The EPC in a regular barcode - source: TEC-IT

Figure 2-8: The same EPC code in a 2D data matrix - source: TEC-IT

2-3-2 RFID

RFID is the abbreviation of Radio Frequency IDentification. "RFID is a means of storing and retrieving data through electromagnetic transmission using a radio frequency compatible circuit" [Seol et al., 2016]. Compared to barcodes, RFID yields significant advantages such as the ability to read the tags without being in the line of sight, high-speed reads, dual modes of reading and writing on tags, unit-specific identification and the ability to store more information [Seol et al., 2016]. These advantages contribute to their widespread of applications in and interests from various industries, including the retail industry. Barcodes and RFID belong to a numerous group of technologies named under the term Auto ID, which stands for Automatic Identification. Other technologies in this group are magnetic inks, optical character recognition, voice recognition, touch memory, smart cards, bio-metrics, etc [Ilie-zudor et al., 2006]. Auto ID can be used for automatic identification of objects, products, persons or animals.

The history of RFID

The origin can be traced back to the second world war, where it was used to identify if incoming planes were friend or foe. This distinction could not be made using radar conventionally. The Germans discovered that if pilots rolled their planes on returning, the radio signal that reflected back would change. Basically, this was the first passive RFID system. The British later developed the first active RFID system to identify its planes. The first examples of the use of RFID in different industries are Electronic Article Surveillance (EAS) tags, which were used on products as an anti-theft system. It contained one bit which could be on or off, dependent whether there was paid or not. Another example is the identification of livestock, where the RFID tag is the yellow tag in their ears. It was developed to track which cows already got their doses of hormones and medicines. However, it could also be used for other purposes such as which cow arrived at the milking station. The milking station recognises the cow and keeps track of how much milk she produced. Over the years, more development in the field RFID was done. Higher frequencies were used, enabling more and more applications. Eventually, large companies started to support the Auto-ID centre and an EPC was developed. Hereafter, large retailers started to use RFID to identify their merchandise [Roberti, 2005]. The first uses were mainly on the pallet- or case-level tagging. Nowadays, a majority of the retailers who have multiple stores are looking into the possible uses of RFID for item-level tagging. Surveys among 60 soft lines retailers and wholesalers with revenues of $500 million plus shows an increase from 34% in 2014 to 73% in 2016 of the respondents that had implemented or were currently piloting RFID ([Salmon, 2014],[Salmon, 2016]).

Comparison between barcodes and RFID
The differences between barcode identification and RFID are summarised in Table 2-1.

Table 2-1: A comparison between barcode identification and RFID - based on source: AB&R

	Barcode	**RFID**
Line of sight	Required	Not required
Read range	Up to several meters	Passive up to 10-15 meters Active up to 100 meters
Read rate	One at a time	Up to 1000's simultaneously
Identification	Type of item (UPC)	Unique item (EPC)
Read/Write	Read only	Read and write possibilities
Technology	Optical (laser)	RF (Radio Frequency)
Interference	Obstructed barcodes can not be read (dirt, torn, object in the way)	Several RFID frequencies do not match with metals and liquids
Automation	Labour intensive (often)	Automated (often)
Price	Cheap (less than 1 Euro cent)	Passive (6-8 Euro cent) Active (Several Euros)

2-3-3 Principles of RFID

A RFID system usually contains two components, namely a tag and a reader. The tag is mounted on the item that has to be identified and has a unique identification code. This identification code contains information about the identity of the product. Each tag has a unique identification number. The tag can contain other relevant information as well such as the manufacturer, country of origin and expiration date. The reader can write data to and read data from these tags through wireless transmission [Seol et al., 2016].

Passive and active tags
Many types of RFID tags exist, but at the highest level, RFID tags can be divided into two categories, passive and active tags. Active tags require a power source, either they are connected to a powered infrastructure or use energy from an internal battery. Passive tags do not require a direct power source. With passive tags, the reader is responsible for powering and communicating with the tag [Want, 2006]. Active tags have a stronger signal, are bigger and can be read from up to 100 meters. However, passive tags are a lot cheaper, and their performance is sufficient for the apparel retail sector. Therefore, most of the new projects with RFID in the apparel retail are using passive tags. The basic principle of how a RFID identification system with passive tags works is shown in Figure 2-9. In the retail are mainly disposable passive tags used, which are shown in Figure 2-10. As seen in the figure, a barcode and other relevant information can still be printed on the same label.

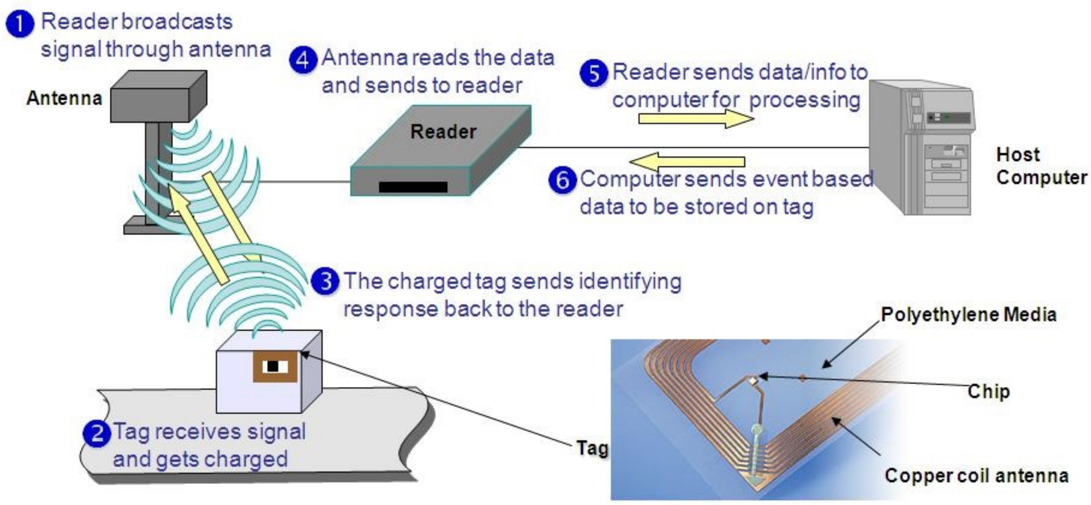

Figure 2-9: How identification with the use of an RFID works - source: TATA consultancy services

Figure 2-10: Passive RFID tags - source: Sparkfun

RFID-readers

Figure 2-9 shows an antenna, which is directly connected to a reader. In the situations of a passive tag, the antenna sends out radio waves. These radio-waves are picked up by the tag and used to power the tag and send back a radio wave with their identification number. This signal is received by the antenna and read by the reader. In the situation of an active tag, the tag has a power supply to send radio waves. The reader can communicate with the host systems, which can link the received identification numbers with products. This communication is often one way, and step 6 is therefore optional and often not used in stores. Readers are often combined with antennas and come in multiple forms. The ones often used are handheld readers, table readers, gate scanners or fixed readers. All of which are shown in Figure 2-11. Another reader that is developed in the last year is the robot reader. It is basically a robot on wheels with fixed scanners mounted on it. The robot is able to scan the whole store overnight by autonomously moving around. An example can be seen in Figure 2-12. The different RFID-readers and the information they can obtain are analysed in Chapter 5.

Figure 2-11: Multiple RFID readers used in the apparel industry - source: Vance

Figure 2-12: An RFID-tag reading robot - source: RFID journal

Adoption by the industry

The ability to identify unique objects enables RFID applications in various industries. Some examples are the identification of livestock, the ability to track people during a race or at a convention, the ability to identify persons with a tag in their passport, wireless payments, tracking and identifying assets in supply chains, warehouses and storages. The ability to identify assets is the primary use of RFID in retail stores.

2-4 RFID in the apparel retail industry

RFID already exists for many years. However, in the last 5 to 10 years, it gained much attention among apparel retailers, where in the last 1 to 3 years most retailers started to think about pilots or implementations. There are a couple of reasons for the rapid gain in momentum the last years. The retail sector has conducted many pilots and learned many lessons. The retail sector, in combination with universities, has established standards and the technology has matured. Both resulting in improved performances and a vast reduction in the costs. Digitalisation and the rapid development of software have resulted in many applications and integrated systems. All of these factors in combination with the recovery of the economy from the financial crises have resulted in a rapidly growing demand for RFID systems, where the reduction of the costs is the primary incentive.

RFID from manufacturer to retailers
RFID can be used from manufacturer to the end customer. At the manufacturer or distributor, it can be used for cycle counts of finished products, order picking and shipping auditing.

Throughout the whole supply chain, products can be followed and identified with the use of RFID. Especially in-store, which is a big black box regarding tracking and identifying products without the use of RFID. With the use of RFID, it is possible to count and identify the products directly at the receiving point, do fast and accurate stock counts in the storage and on the sales floor, find products faster, protect merchandise against losses and theft and improve the point of sale process. Hence, RFID can vastly improve the information obtained and thereby improve processes or solve problems. Even new processes and sale methods can be developed.

Adoption by major retailers
The research of [Salmon, 2016] analyses the current adoption by the biggest soft lines retailers and wholesalers, with revenues of at least $500 million in the US. It analyses some use cases and the top metrics measured to capture RFID's impact on Return On Investment (ROI). It concludes that the adoption rate by the major retailer is increasing and that retailer who waits to adopt RFID will fall behind their competitors. The major retailers are precursors in the adoption of RFID, because setting up a pilot store or investing a significant amount is relatively easy for them.

Use cases for RFID
The research of [Rizzi et al., 2016] has carried out a comprehensive literature review of 160 papers on RFID-deployments in fashion and apparel retail. It has structured all papers in a framework containing six categories and 18 different use cases:

- **Shop floor management**
  - Locating items
  - Prevention of loss
  - Point of sale transactions / faster checkout
  - Stock visibility / replenishment from the backroom
- **Customer relationship management**
  - Social shopping
  - Know your customer / store associate availability
- **Marketing and promotion management**
  - Customer experience
  - Cross selling / cross promotions
  - Store associate empowerment
- **Logistics management**
  - Process automation
  - Process accuracy
  - After sales / returns
- **Inventory and supply chain management**

  - Inventory accuracy / out-of-stocks
  - Omni-channel retailing
  - Supply chain visibility

- **Brand protection**
  - Grey market
  - Counterfeiting
  - Trace-ability

Although the categories are divided into separate use cases, papers often discuss multiple simultaneously, and many are dependent on or enable each other. However, not all are equally important to retailers.

2-5 The main reasons to adopt RFID

The main reason to adopt RFID is to obtain more frequent and accurate information to enable improved replenishment and thereby reduce the number of OoSs. The drive of reducing of OoSs is based on the fact that retailers can not sell an item directly if that item is unavailable, resulting in lost sales and revenue losses. According to [ChainLink, 2014] the top reason for implementing RFID is *improve inventory accuracy* (see Figure 2-13). This makes sense since it is the basis for most improvements. The second reason for retailers to adopt RFID is to reduce the number of OoSs. Although other studies sometimes list priorities somewhat different, mainly due to the style of interviewing, they provide more or less the same key reasons for implementing RFID. The arguments can all be linked be to the core drivers for improvements in the retail: increase sales and process efficiency. They are in the end the fundamental core financial drivers for most RFID implementations [ChainLink, 2014]. The focus of this research is on the improvement of store replenishment to reduce the number of OoSs.

The question here is if an unavailable item always results in a lost sale. For example, a black shirt can be substituted with another black shirt, a 1 kg of sugar can be easily replaced by two times 0.5 kg or even a different brand. Sugar is sugar. However, a Feyenoord shirt will not be substituted for an Ajax shirt. The same accounts for sizes, a person that usually wears large shirts, can not buy two small ones.

Magnitude of OoS situations
In the literature, almost every study points to the study of [Gruen et al., 2002] for the reaction of customers to OoS situations, including most studies regarding apparel retailers. The study provides that out-of-stocks vary widely among different retailers, with an average of 8.3% worldwide (8,6% in Europe). The reactions of customers to OoS situations are given in Figure 2-14. The drawback of the study of [Gruen et al., 2002] is that it studies different types of Fast Moving Consumer Goods (FMCGs) instead of apparel. The reactions to OoSs for apparel as well as the percentage of OoSs can be significantly different. Studies explicitly naming apparel retail stores present the following OoS percentages: 30-40% [Vermin,], 8-20% [Stelter, 2015], 15-20% [Salmon, 2013] and 16.5% in [Salmon, 2016]. Although the reactions

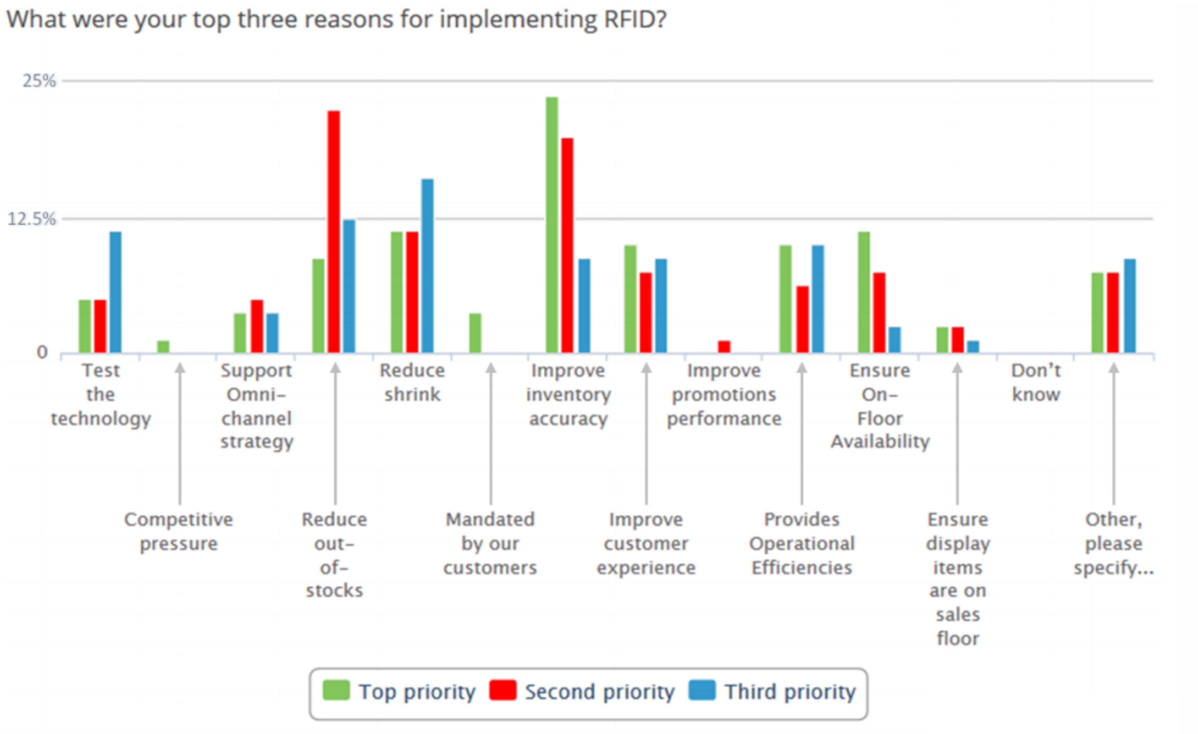

Figure 2-13: Top reasons to implement RFID - source: Chainlink Research

to and percentage of OoSs can significantly differ, it is clear that it is a problem that results in lost sales.

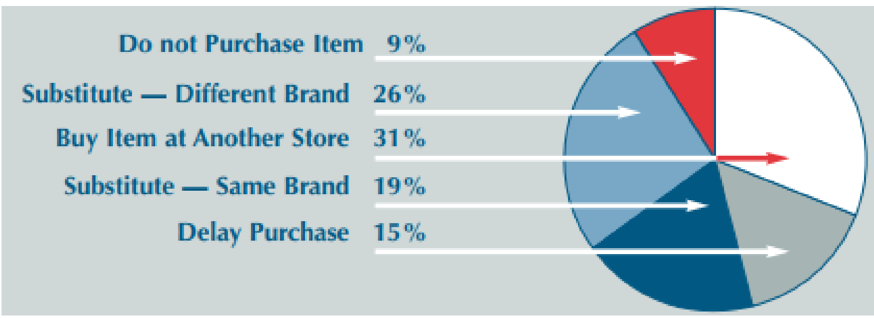

Figure 2-14: The response to an OoS situation for retail in general - source: Retail Out-of-Stocks: A Worldwide Examination of Extent, Causes and Consumer Responses

Web-rooming

The problem is even increasing, because of 'web-rooming' that is becoming more and more important. Web-rooming is the practice of researching items online and then purchasing them in-store [Säilä, 2016]. The research of [Footfall, 2016] even suggests that 55% of the shoppers who walk into the store know exactly what they are looking for. The reasons are that customers do not want to wait for products, pay for delivery or make unproductive trips to stores. As a result, having in-store availability or the opportunity to tell customers how many are left in-store with improved certainty is becoming more and more critical.

Conclusion

In this chapter, the transformation of the retail industry, from single-channel to omni-channel retailers, is explained. In the early days of retailing, the choice for customers was limited and apparel retailers could determine what customers were able to buy. Nowadays the amount of apparel retailers, online as well as offline, is almost unlimited. Customers are not bonded to a specific retailer and are expecting the best features of online and offline retailers combined, such as a high variety of products that are always available. Especially, in the apparel industry, where substitutions are less often made because of the specific models, brands loyalty, sizes and the 'web-rooming' effect. Therefore, retailing has become more customer-centric. Retailers have to provide these customer requirements. To meet the demand of a high variety of products that are always available, retailers have to improve their replenishment. Extra information is necessary to achieve this. The use of sophisticated Auto ID technologies, such as RFID to obtain the necessary information, is gaining popularity due to the increased technology maturity level and the decreased costs. RFID in apparel stores can be used for many applications. Regarding store replenishment, it can be used for receiving items, locating items, counting inventories more accurate and faster, scanning items at the check-out, theft prevention and identifying unique items. The most important one is counting inventory to create item visibility because this forms the basis for an improved replenishment, that can reduce the number of OoSs. The next chapter presents a literature study regarding RFID-based replenishment in retail stores to determine to what extent the topic already is covered.

Chapter 3

Literature

This chapter presents a literature study into RFID based replenishment in retail stores.

The chapter answers the following research question:

What elements of RFID based replenishment in retail stores are discussed in the literature?

The chapter starts with summarising different studies and highlights their key findings. The second part presents the conclusions and differences between this research and the literature.

3-1 Studies on RFID based replenishment

The following section summarises several studies on RFID based replenishment

RFID enabled shelf replenishment - theory
In [Wong and McFarlane, 2007] is described how the final few meters of a supply chain are critical to the performance of the whole supply chain. The research, therefore, focuses on shelf replenishment in retail stores. The motivation for the research is that the automatic identification technology Radio Frequency IDentification (RFID) is emerging in the retail. The paper describes two replenishment controls, which are linked to manual barcode and RFID data capture strategies. It lists several strengths and weaknesses of each method. The research determines, based on literature, which factors influence the effectiveness of these policies. Specifically, the issue of timeliness of information, decisions and operations is assessed to determine the potential impact of RFID technology on shelf replenishment. The research focuses on grocers and only explains the theory. No quantified data is used or calculations are made. The paper provides an overview of future research and does not draw any conclusions regarding the performance of different policies. However, it does acknowledge the potentials of RFID-based replenishment models.

RFID enabled shelf replenishment - simulation study
In [Thiesse et al., 2007] a simulation study of RFID enabled shelf replenishment is described. The research tries to quantify the value of RFID data in the Fast Moving Consumer

Good (FMCG) supply for the shelf replenishment process in retail stores. It presents a simulation study on the impact of improved data quality on product availability. The research shows how RFID allows for the redesign of in-store processes, which perform more efficiently regarding profits and Out of Stocks (OoSs) depending on the technology costs and capabilities. Furthermore, influence factors are considered, such as personnel costs, inventory holding costs, product demands and other logistical characteristics. The research also shows that in many cases the maximum benefits can only be drawn from RFID if decisions on the optimisation of shelf space are being made in parallel. However, the research studies case-level tagging of FMCG in grocers, instead of apparel retail stores which focus on item-level tagging. The simulation does not take any errors into account, assumes that the stock levels are always known, is only based on one product, namely razor blades.

RFID enabled shelf replenishment - imperfect read rates
The research of [Condea et al., 2012] is concerned with the value of RFID for retail store operations, particularly the use of the technology to automate shelf replenishment decisions. The study focuses on an inventory control policy based on RFID data with case level tagging. In addition to the prior research, the research takes detection errors caused by imperfect RFID read rates into account. The results indicate that RFID-based policies have the potential to improve cost efficiency and service levels. However, different sensitivities to cost factors and sub-optimal read rates must be considered when choosing a policy. Since, imperfect read rates can influence the results, mainly in case level tagging. As in the research above, this research also takes only one product into account and uses case-level tagging.

Visual- versus RFID-replenishment for case- and item-level tagging - simulation study
In [Thiesse and Buckel, 2015] prior researches are extended. In this research, factors as design choices, technology characteristics, and external influences are taken into account. The study aims to analyse and discuss the influence of these factors on the economic efficiency of RFID. In this research, item-level tagging is taken into account. The research acknowledges promising benefits regarding in-store replenishment with the use of RFID. However, it also considers the challenges. The challenges listed are the types of tags used, from simple labels to robust tags with memory and sensors. The implementation level, in some cases item-level tagging is used, whereas others rely on case-level tagging. The research also states that RFID has its physical constraints, especially with metallic or liquid products and concludes that sub-optimal read rates have a significant impact on the data quality. The research compares two types of replenishment, namely replenishment based on periodic visual inspection and RFID based replenishment. In both situations, two types of tagging are compared. Simulations for different read rates and other relevant parameters are performed for each combination. Different read rates result in different operating costs, a higher read rate thus results in lower operating costs. Variables as tag costs are also implemented. The conclusions are that both levels of tagging may allow for implementing shelf replenishment processes in stores that outperform replenishments with visual counts. However, there are significant differences if different read rates are taking into account. The costs of case-level tagging substantial increases with a decrease in read rates, this effect is limited in item-level tagging. Other factors as misplacements and thefts are appointed, but not taken into account. According to this research, RFID tagging is useful as long as the read rates are high enough, mainly with case-level tagging. Only one item is taken into account in this research, where on average ten a day was sold from. The assumptions made are based on a combination of data from

two grocers and two apparel retail with totally different retail processes. The fact that read rates are not perfect is mainly caused by water and metal interferences. Which occurs a lot in grocers. In apparel stores, none of the items is made out of water or contain large metal objects. In apparel stores, item-level is used, which is less sensible for lower read rates.

Influence of RFID on sales turnover - pilot store
The paper of [Bertolini et al., 2012] executes an experimental evaluation of the business impact of RFID in apparel and retail supply chain. In this research the results of an experimental campaign carried out in Italy in 2010 are used. Approximately 20.000 garments were tagged, which were shipped to one retail store of a major Italian fashion brand. These tags were followed by mobile and fixed RFID readers and the collected data was used for this research. The research proved that productivity for item checking with RFID could be increased by almost 90%, enabling a more frequent inventory count. Furthermore, the study concluded that with several quick inventory counts an inventory accuracy could be obtained between 97% and 99,54% depending on the circumstances. Circumstances which could influence the accuracy are for example items with metallic fabrics, other large metal objects, humans and the density of items per area. However, the paramount outcome of the research is found in the estimate of RFID impact in turnover of the retail store. The increase in turnover was caused by two contributions. The first one is the availability of information about what is available in the backroom. Employees could directly know what is in the backroom and sell these items. This resulted in an increase in turnover of 0.8%. The second contribution is the possibility of optimising the replenishment from the backroom to the sales floor by real-time information, which resulted in an increase in turnover of 4.91% to 11.1% depending on the chosen time slot regarding the direct selling as a result of the replenishment.

Influence of RFID on sales turnover - pilot store
The research of [Bottani et al., 2016] provides evidence that a RFID-based replenishment policy improves sales turnover in fashion retailing. The study first highlights a few prior researches where claims are made about the improvement of sales with the use of RFID. It investigates these improvements with the use of a pilot project in a fashion retail store in Italy. The research uses RFID technology to present a daily list of sold out products on the sales floor, which are available in the backroom to replenish. The research finds that an increase in availability leads to a significant increase in the sales volume. A second conclusion made is that the availability of products on shelves stimulates customers to ask for different sizes and models, generating further potential for sales increase, because this store did not displayed all the models and sizes on their sales floor. The pilot determines the pre-RFID situation, where the store is replenished before the stores opens. It then proposes a RFID system with three gates at the delivery point in the backroom, between the backroom and sales floor and at the Point Of Sale (POS). To compensate errors, employees used handheld readers twice a week to update the inventory manually. The research only followed ten different items, during the weekdays. The research did not take any economic value or other influencing factors into account and only updated the replenishment lists. The store manager still decided by himself which items were to be restocked and the replenishment frequency did not change. The research showed a positive result regarding an increased sales turnover for the RFID-deployment. The results where an increase in sales volume ranging from 4.72% up to 9.16% depending on the clothes category. The research used products that were frequently sold.

Influence of RFID on staff assisted sales - simulation study
The research of [De Marco et al., 2014] models the effectiveness of RFID technologies in

improving sales performance in fashion outlets. The study acknowledges the potentials of RFID but describes that there is a lack of research into item-level tagging in stores. The research is executed for an Italian retailer, where staff-assisted sales play a significant role. The research mainly focuses on the influence of RFID regarding the reduction of the time it takes for employees to do specific processes which are not directly linked to staff-assisted sales, such as receiving goods. It then relates the saved time to increased staff time for customers, which increases sales. The conclusions are that implementing RFID will result in an increased number of sales if the economic climate is favourable, due to the extra available staff time. On the other hand, the research even concludes that with a less favourable economic climate, RFID could still generate benefits in term of decreased personnel costs. The research uses RFID handheld readers as only RFID-deployment. It leaves out other potential benefits such as theft prevention, check-out automation and faster locating of items.

3-2 Conclusions from the literature

The following conclusions can be made from the described literature studies:

- RFID has the potential to improve the sales turnover, mainly by increasing item availability.
- OoS has several definitions in different researches. In the research of [Condea et al., 2012], OoS is considered as 'in stock but not on shelf' and in the research of [Wong and McFarlane, 2007] OoS is defined as the temporary unavailability of products in the retail store. Definitions of concepts as OoS are defined in the next chapter.
- Sub-optimal read rates play a role for grocers where products contain a lot of metal or water and/or when case-level tagging is used. For item-level apparel tagging, it is less relevant, especially with the still improving technologies. Read rates can, therefore, be close to 100% and are assumed to be perfect in the rest of the research.
- RFID enables faster inventory counts, enabling inventory counts to be performed more often without closing the store.
- Although the study of [Wong and McFarlane, 2007] is about FMCGs, it is clear that the final few meters of a supply chain, the replenishment from backroom to the sales floor, are critical for retailers to sell their items to customers.
- The researches mainly study handheld readers, apart from the research of [Bottani et al., 2016] where RFID-gates are studied. Other RFID-deployments are not discussed.

The following differences between the studied literature and this research became clear:

- Many studies were focused on FMCGs and grocers instead of apparel retailers ([Wong and McFarlane, 2007], [Thiesse et al., 2007], [Condea et al., 2012]). In [Thiesse and Buckel, 2015] a combination of grocers and apparel retail stores was used. In reality, processes, prices, replenishment strategies, product quantities and reactions of customers differ significantly in apparel stores.

- Item-level tagging was only considered in half of the researches of which two were pilots. Although case-level tagging can be sufficient for some use cases, item-level tagging is necessary for apparel retail stores. The main reasons are costs of the products, the high variety of products in low quantities and the fact that most clothes do not arrive in cases.
- Apart from the pilots ([Bottani et al., 2016], [Bertolini et al., 2012]) and the study of [De Marco et al., 2014], the researches were focused on one single product with high quantities and high sales rates instead of a store with many different products in low quantities.
- The researches were not specific about RFID, in reality, many different types of RFID readers and systems can be implemented to obtain different levels of information. A full RFID implementation with overhead readers was not taken into account.
- Studies often only looked at the replenishment in-store with an unlimited backroom or took the store as one element instead of dividing it into a backroom and a sales floor.

3-2-1 Research gap

In general, can be concluded that RFID has the potential to improve the replenishment process and reduce OoSs in theory. This is supported by fundamental research, which is often focused on one FMCG. On the other hand, there are pilot projects in real stores, which also show the benefits of RFID. However, in between fundamental research and a long-running expensive pilot project is a research gap. This gap is shown in Figure 3-1.

Figure 3-1: The research gap

The research gap forms the basis for this research. The main differences between fundamental research and this research are that different RFID-deployments, store configurations, item-level tagging and apparel in specific are taken into account. The difference between pilot stores and this research is that pilot stores are specified to one specific store, excluding all other types. Simultaneously, a control store is necessary and parameters and deployments can not be adjusted and tested directly.

Since every retail store is unique. The implementation of RFID can for example have different results for a small shoe store, than a large chain store. Furthermore, there are multiple RFID-deployments resulting in different levels of information, which can also influence the number of OoSs per retail store. This research fills in the research gap with the following main research question:

To what extent does more information, obtained by different RFID-deployments, result in less out-of-stocks for various apparel store configurations?

Relevance of the research

A cost-benefit analysis is normally made before starting a large project. In order to deploy RFID, a retailer wants to know the benefits and drawbacks to a certain level of detail. An advertising leaflet that claims for example 30% improvement in the reduction of OoSs is insufficient, on the other hand a pilot project is for retailers often a step too far or too expensive. Especially when an indication of the benefits can not be made. The same accounts for different levels of RFID-deployments and corresponding costs. The most extensive and expensive RFID-deployment often results in the highest level of information. As a result, the most significant improvements are possible. However, for a specific purpose or retailer requirements such a high level of information is not always necessary and is not always worth the investment. A cost-benefits analysis is out of the scope of this research. However, it should be taken into account when implementing RFID. This research gives insight into one part of the cost-benefits analysis, namely the benefits of RFID regarding the reduction of OoSs. All the other factors that normally should be taken into account for a comprehensive analysis are given in Appendix B-3.

Conclusion

The literature presents several studies regarding replenishment but often uses only handheld readers as RFID-deployment with one type of a FMCG in combination with case-level tagging, instead of item-level apparel tagging. The only studies that use item-level tagging for apparel stores are studies regarding pilot projects. What is missing is a study that compares different RFID-deployments for various apparel store configurations. The next chapter analysis the retail store including the problem in detail.

Chapter 4

System and problem analysis

The following chapter analyses a retail store as a system, explains the problem in current retail stores in detail including the relevant performance indicators and enlightens the research problem.

This chapter answers the following research question:

What is the current problem in retail stores, what is more information and how can it be used to solve the problem?

It does this by analysing a retail store as a system in detail including the Key Performance Indicators (KPIs), providing the importance of more information obtained by Radio Frequency IDentification (RFID) and explaining the relevance to Out of Stocks (OoSs).

4-1 Analysis of the system

The most common type of retailer is a mortar and brick store. In the rest of this research, it is assumed that the retailer is a mortar and brick store, shown in a supply chain in Figure 4-1. The store has a distributor to supply the stores' merchandise and sells its merchandise to end customers. The other steps of the supply chain are not taken into account. The store is first seen as one system, where after a zoomed-in analysis is made.

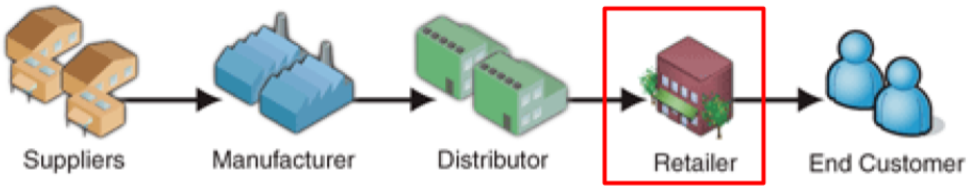

Figure 4-1: The focus is on the mortar and brick retailer - source: Microsoft

The store as a system

A system is defined by [Veeke et al., 2008] as: *"a collection of elements that is discernable within the total reality. These discernable elements have mutual relationships and (eventually) relationships with other elements from the total reality"*. The group of elements chosen to study as a system within the total reality is dependent on the research goal. In this research, the group of elements chosen to study is a mortar and brick store. The mortar and bricks of the store are literally the system boundaries. The direct environment of the system consists out of a distributor and end customers. Due to the interaction with its environment, the system is an open and time-dependent system.

Black box

The basic concept of a store as a system can be explained with Figure 4-2. The black box, represented by the grey area, is the mortar and brick store. The system boundary is presented by the black line around the grey area. The input of the black box consists out of items from a distributor and customers without items. The output consists out of customers who have bought items, customers who have not bought any items and unsold/lost items, for example through theft. The black box presents a simplified overview of the retail process. In reality, items can also arrive from other stores and customers can return items. Items can also leave the store sold without any customers, if for example the item is sent to another store or sold and send to the customers home. These processes are often only a small percentage compared to the other flows or even excluded. The black box in Figure 4-2 is assumed to be an representation of a retail store as a system on the highest level.

Figure 4-2: Black box of a store

The retail process

In between the system boundaries is the retail process. A process is defined by [Veeke et al., 2008] as: *"A process is a series of transformations that occur during throughput which result in a change of the input elements in place, position, form, size, function, property or any other characteristic."* In the situation of a retail store, items go through the process. The first change is the position of items that enter the store. Starting at the supply point of the store, going through the store and leaving the store at the main entrance. In exceptional situations, the items can also leave the store through the supply point or other exit points. The second change that takes place in the process is property, the items enter the store as a property of the retailer and leave the store in most of the situations as property of a customer. The third change is the function of the items. The items enter the store as merchandise and leave the store as an item used for body cover or/and for fashion purposes. The second input of the Black Box is customers. The customers come in the store to buy items, they leave with or without items.

The goal of a retail store

The function of a retail store is selling the items that enter the system to the end customers in order to make a profit for the store owner. Subsequently, the goal of the system is to sell as many items as possible in order to make the most profit or at least a sufficient number, in order to survive the competition. Increasing the profit can also be achieved by improving the retail processes in order to increase the margins on products. In exceptional cases, stores can have another main goal, such as branding products or launching a new marketing campaign. In such a situation, making profit is not their main goal. In the rest of the research is assumed that the goal of a retail store is to make profit, where extra profit is desirable. Customers can not buy items that are not available. Increasing item availability and thereby reducing the OoSs will increase the sales and consequently increase the profit.

The performance of a retail store

The input of the function is items owned by the retailer, the output is sold items owned by customers. In order to determine if the system functions properly or to measure improvements,the requirements and the performance must be established. A requirement of a retail process could, for instance, be to maximise profit. The performance is then measured in profit, which could be measured as a concrete number or compared to historical profit. In more detail, the profit can be obtained by selling more items or improving margins.

Assuming that the customers come in with a pre-determined desire for a specific product or size, one way of increasing profit is to reduce the number of OoSs. The requirement could be defined as a decrease in OoS compared to a reference situation or as a concrete number. For example a maximum of 5%. At the same time, multiple requirements have to be taken into account. For example increasing the inventory with a factor 10, would probably also reduce the number of OoSs. However, this is often not desirable due to limited space and inventory costs.

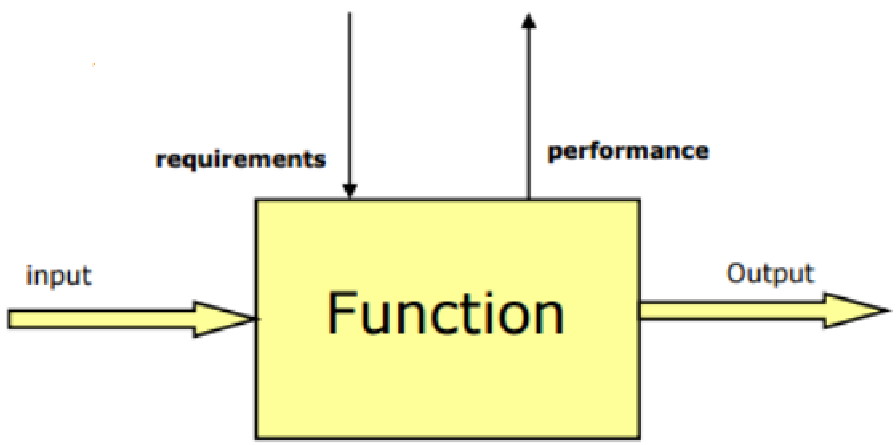

Figure 4-3: The function of the system - source: DSA

Key performance indicators

KPIs are the most important metrics in a business. It allows retailers to measure the performance of their retail store. Various KPIs can used in retail stores, based on what needs to be measured or what the strategy is. Some commonly used KPIs are: sales, customer returns, transaction counts, labour costs, inventory-to-sales ratio, inventory turnover rate, return on capital employed, gross margin return on investment, OoSs, average inventory, inventory accuracy, customer satisfaction, sales per m^2 and transaction value.

In this research, aspects as the customer experience and the financial situation of a store are left out. The KPIs selected are used to measure the performance of the system and are all related to inventory and inventory availability.

The main KPIs are:

- Percentage of OoSs
- Average inventory
- Inventory accuracy

Other performance indicators that could be used in a retail store to measure the performance are constant in this research:

- Inventory turnover rate
- Lead time
- Inventory losses
- Number of customers
- Customer demand

All KPIs are explained in the next section.

The system in more detail

In order to get a deeper understanding of the system, the retail store is investigated in more detail. The first distinction made is the segregation between a customer-facing sales floor and an operationally-focused backroom area, which is the situation in most retail stores [Fisher, 2004]. The backroom of the retail store is the area where the items arrive and are stored until required on the sales floor. If items are necessary on the sales floor, items are moved from the backroom to the sales floor. The items are showed and stored on the sales floor in order to be able to sell them. The sales floor is the area where customers can see, check and pick-up their items. The two areas are shown in Figure 4-4. The figure contains four arrows, representing the following flows:

1. Items arriving at the store (to-store replenishment).
   - Almost all items arrive at the backroom of the store at a supply point. Normally, a few can arrive through customer returns, these are left out in the rest of the research.

2. Items that are replenished in the store (in-store replenishment).
   - The items that are being replenished from the backroom to the sales floor.

3. Customers arriving at the store.
   - Customers arrive through the entrance of the store. Normally without any items, although they can arrive with items to return them. However, returns are left out in the rest of the research.

4. Items and customers leave the store.
   - Customers leave the store with or without items.

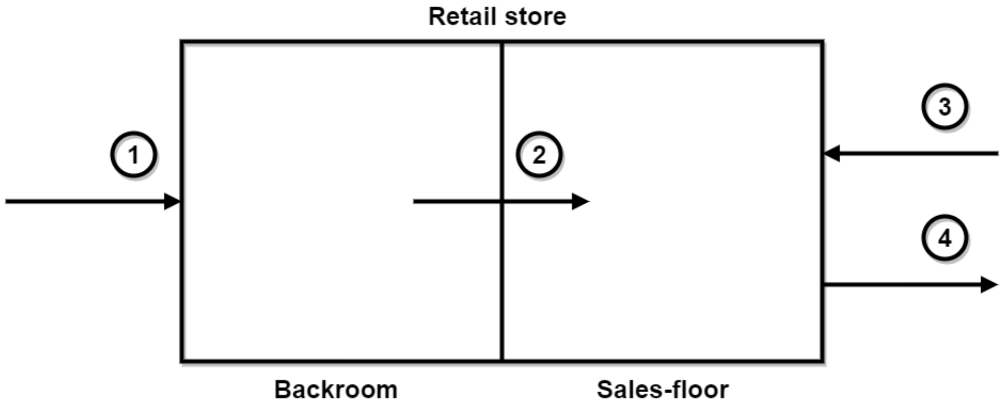

Figure 4-4: A schematic view of a retail store with a backroom and a sales floor

Elements of the system

In-store, several different elements exist to execute the retail process. The most important ones are discussed. Figure 4-5 shows an apparel store layout with its basic elements. The backroom has an area to receive items and a storage area. From here, items are moved to the sales floor. The sales floor has shelves and racks to store and show items. From the shelves and racks, the items can be picked up by customers and moved to the fitting rooms or directly to check-out. At the check-out, the customer can pay for its items where after they can leave the store. In some cases such as theft, items are directly moved through the exit.

The process of the retail store shown in Figure 4-5 is schematically shown in Figure 4-6. In reality, more flows or elements can exist. The difference between the figures is that shrinkage is added, which is mainly a result of employee and customer theft. Customers and employees are shown on top. Employees are involved in the whole process. Customers only on the sales floor part. The different sub-processes are schematically shown and the arrows between represent movements of the items performed by customers or employees.

All the sub-processes and elements are described in short below:

- **Goods receiving** - Items are received here and often stored in the backroom until they can be replenished.

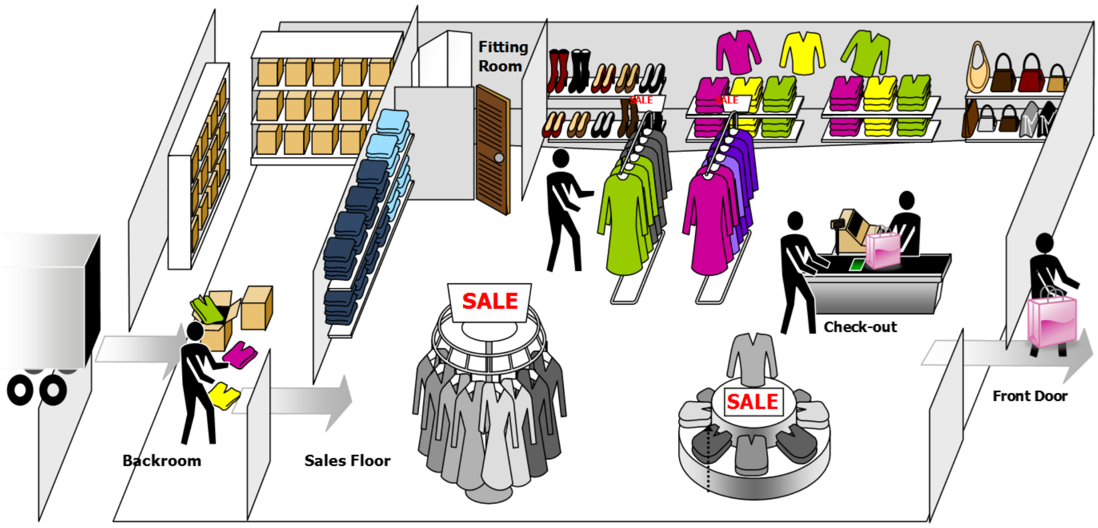

Figure 4-5: The basic elements of a retail store - source Mojix

- **Backroom** - The backroom is used as storage, where items are kept until necessary on the sales floor.
- **Restocking** - The restocking process is the process of moving items from the backroom to the sales floor.
- **Sales floor** - The sales floor is used as storage and showroom, from where customers can buy items.
- **POS** - If customers have picked their items, they can go to the check-out and pay for their items at the Point Of Sale (POS).
- **Shrinkage** - Items that leave the store without being paid for. This can be due to theft (internal as well as external), lost items, off-season write offs.
- **Employees** - Employees support the whole process and move items around.
- **Customers** - Customers pick up and move items around on the sales floor and go through the POS process to purchase their items.

4-1-1 Store control

The high competition and extended customer demands in the retail sector cause retailers to struggle. Where decades ago the retailer decided what he wanted to sell and the customers did not have many choices, nowadays retailers have to have a high variety of items that are available and have to continuously adapt to keep their customers. Many elements can be thought of: from changing their store concept, to re-branding, increasing publicity and changing the store layout to lure customers to purchase more.

However, the bottom line is: in order to sell items, they have to be available on the sales floor. The basics of how a retail store is controlled is explained in this section. In reality,

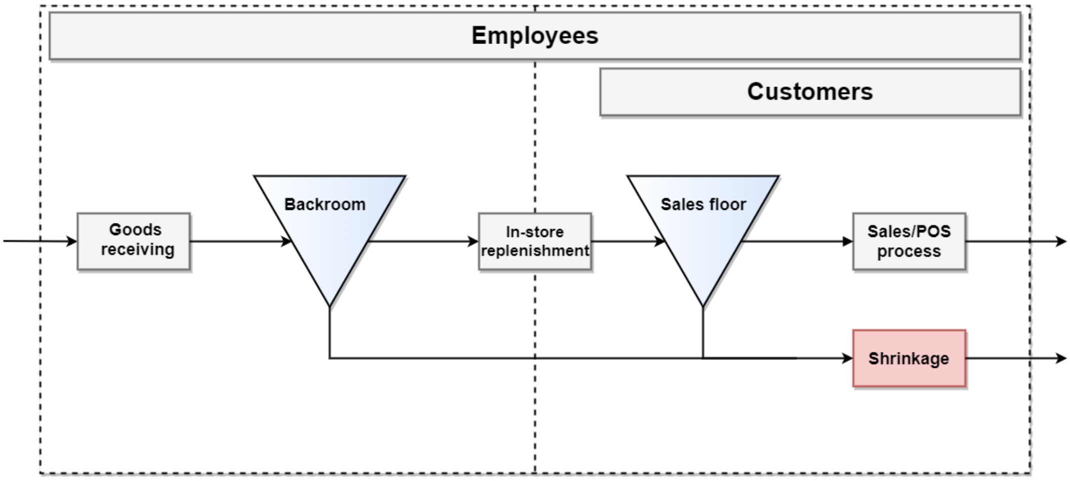

Figure 4-6: A schematic view of a store

more elements determine if items will be available and if customers purchase them. Such as: weather, trends, prices, kindliness of staff, competition in the area, but these are left out.

Item availability

For retailers to sell items and make a profit, one of the key elements is a correct quantity of each product. Insufficient items can result in OoS situations and as a result lost sales. Too many items can result in extra holding costs and lower margins because of unsold items. In essence, controlling a retail store sounds simple. If an item from the sales floor is sold, replace that specific item from the backroom. Reorder the item if the number of items in the backroom is under a chosen threshold value. Discussions or calculations about the restocking frequency and reorder sizes are necessary, but the system will work and the OoS situations will be minimal. However, an example will explain the problem with this control. Lets say that there is a small store where the owner sells a limited amount of products, including red sweaters in one size. The retail owner himself is continuously present in the store and he can directly replenish a red sweater if he sells one. He probably also knows how popular the red sweaters are. Therefore, he is able estimate when and how much red sweaters he must order if the level of items in the backroom is low. The solution of replenish an item that is sold and reorder items if they are almost sold out will probably work in this example. However, the problem arises if a store has thousands of different products with different selling rates and inexperienced employees alternating each other. For an individual employee, it is completely unknown what is sold, moved and still available in the store. The small store can do a quick visual check to see how many sweaters there are. However, in a larger retail store a fast visual check is almost impossible. An employee can guess the amount of trousers in total or count all of them. However, if there are many models of trousers (skinny, regular, wide, stretch), which all have different sizes (width, length), it becomes almost impossible to count everything. Every item has to be inspected individually on the model and sizes in order to see what is still available. This will take a long time and some sort of administration. Other factors that will also become relevant to larger retail stores are items, which are already ordered or movements by other employees that are unknown to the individual employee.

This problem is well known in the apparel retail industry. In some situations with seasonal clothes, replenishment is not taken into account. Other retail concepts have a different assortment and do not even take replenishment models into account. However, the majority uses inventory systems to keep track of their inventory and to minimize OoS situations.

An inventory system

The inventory is the items that are in the store. This inventory is supplemented with arriving items and reduced with items that leave the system. The most basic inventory system is shown in Figure 4-7.

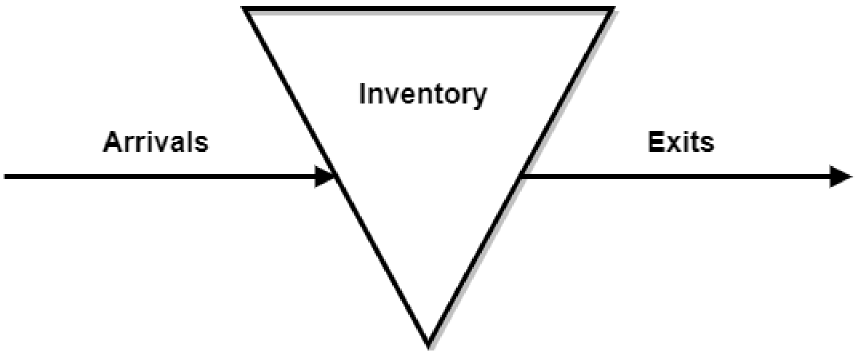

Figure 4-7: A basic inventory system

A basic inventory system works according to the following principle: the number of items at a the beginning of a period $k + 1$, denoted I_{k+1}, is determined from the number of items at the beginning in the previous period, I_k, the quantity received in the previous period, a_k, and the quantity of the items sold in the previous period, e_k. The relationship is given in equation 4-1.

$$I_{k+1} = I_k + a_k - e_k. \tag{4-1}$$

This equation can be used for the total inventory. However, in reality a distinction has to be made between different items in order to determine the amount of each item separately. Each unique item is a so called Stock Keeping Unit (SKU), which determines what item it is. For example SKU-253215: Black trousers, size 32/30, slim fit. Equation 4-1 is unique for each SKU. The total inventory, I_t, is determined by a sum of the total number of unique SKUs, N_{SKUs}, all with their separate inventory records, I_i^k. Determined by the following equation:

$$I_t = \sum_{i=1}^{N_{SKUs}} I_i^k. \tag{4-2}$$

A retail store can be seen as one inventory system. However, in reality most retail stores can be divided between into a backroom and a sales floor and thus can be divided into two sub-inventory systems which can be added together for the total inventory.

Replenishment of an inventory system

The items in a retail store that are sold cause the inventory to drop. Those items have to be replenished on the right time with a right quantity. For all retailers it is key to ensure a high product availability and to minimise overstock or OoS events [Iannone et al., 2015]. Hence, ordering the right quantities in time is key. Even more in apparel retail stores, where customers do not always know what they want, and as a result, higher inventories, through better displays, strongly drive sales [Collado and de Albeniz, 2017]. Although this trend is shifting, it still accounts for a large part of the customers. Therefore replenishment models are of high importance.

The basic elements
The basic elements of replenishment can be explained with the use of Figure 4-8. Replenishment starts with replenishment logic and inventory visibility. Replenishment logic are the 'rules' of when to order and in what quantity. This can only be done correctly if the inventory known (inventory visibility) [Silver et al., 2016]. The level above is order restrictions. For example, orders can only be done on Mondays or there is a minimum order quantity. The top level is forecasting. Forecasting can be useful to optimise replenishment. For example, if a retail store can forecast that product A will sell twice as much as product B, it can already ship two times the original amount of product A in stead of replenishing it twice as much. However, forecasting will not be taken into account in this research. Forecasting is already done in reality, and can later be improved with extra information. However, information about the selling frequency of items and other customer demands is necessary. This study assumes a random uniform demand, with a constant threshold value. The focus of this study is at the direct results of extra item visibility and variations in store parameters.

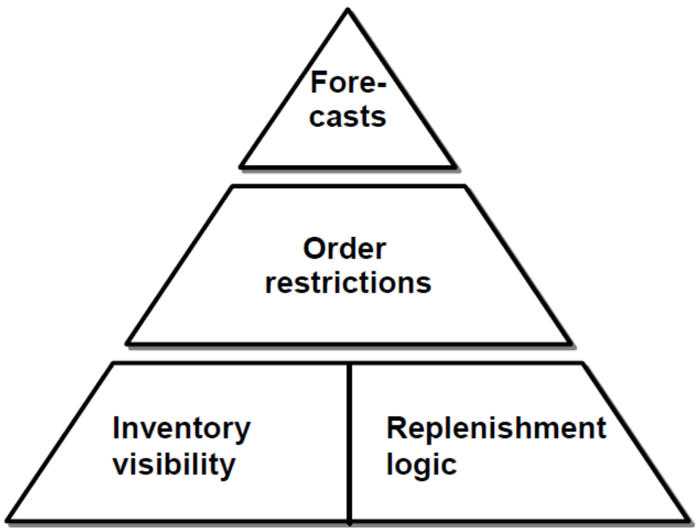

Figure 4-8: The basic elements of replenishment - source: The Impact of Automatic Store Replenishment Systems on Retail

Distinction between sales floor and backroom
Replenishment has to be divided into two parts: store replenishment and shelf replenishment,

in this report named to-store and in-store replenishment. Store replenishment is the supply of stores, where products are delivered from a distributor to the backroom of the retail store. Shelf replenishment is the in-store replenishment from the backroom to the retail shelves. Although it is called shelf replenishment, it is actually supplying in-store shelves, racks, hangers and clothes boxes on the sales floor.

Variations per store
Replenishment can vary for different types of retail stores. Discount stores often buy their inventories at once in large quantities, as a result the stores often lacks a standardised inventory which has to be replenished regularly. Contrarily, supermarkets have a continuous inventory. Products as milk, sugar, bread, etc. have to be available throughout the whole year and are replenished frequently. This accounts for to- as well as in-store replenishment. Apparel retail stores often have a combination of both. The 'Never Out of Stock' products, which have to be available throughout the year and are replenished regularly and temporary collection items, which are often seasonal, flyer or brochure articles are limited replenished or not replenished at all.

Within a certain type of retail store, different types of items can result in different in-store replenishment policies, resulting in different effects. High on-hand inventories can stimulate demand (billboard effect), as can low on-hand inventory quantities (scarcity effect) [Mou et al., 2017]. The policy used is often dependent on the type of store, location, brand, type of products and the ratio between the backroom and sales floor.

Product classifications
Items inside a retail store can also be classified. A regularly used classification is the A,B,C categorisation. Category A accounts for 20% of the total number of items, but represents 80% of the dollar sales volume. Category B items 30% of the total number and 15% dollar value and C 50% on 5% [Silver et al., 2016]. It must be noted that these ratios can differ within the apparel retail industry. As a result of these ratios, it would be logical to give the replenishment of category A products priority over category C. Other replenishment strategies could be applied for different categories of items. For retails with a lack of a standardised inventory, a high sales floor availability and no regular replenishment, improved replenishment strategies with the use of RFID will have limited effects. However, RFID can then have different benefits, such as increasing online sales by accurately knowing the specific inventory. For retailer that replenish their inventory frequently, RFID has the potential to improve the replenishment.

Replenishment logic

Despite all the differences in types of stores and types of products, each standardised inventory has to be replenished. Replenishment first has to be triggered, where after a determined amount can be replenished. In order to trigger a replenishment, the inventory has to be reviewed and compared to a threshold value. If the inventory is equal to or below its threshold value, it has to be replenished. Reviewing can be done periodically or continuous and by visual checks or with the use of data. If a replenishment is triggered, the replenishment quantity has to be determined. There are a number of possibilities to do this, the four most common ones are described in [Silver et al., 2016] and summarised below.

- **Order-Point, Order-Quantity (s, Q) system**
Continuous-review order system. Each time the inventory position drops to the reorder point s or lower, a fixed quantity of Q is ordered or replenished. The already ordered items must be taken into account, otherwise each review extra items are ordered. The advantage is the simplicity of the control and thus errors are less likely to occur. Especially if the two bin principle is used where a second bin corresponds to the order/replenishment point. If the first bin is empty, the item has to be reordered. The primary disadvantage is that if an individual transaction is large, then a replenishment of size Q is not always able to raise the inventory above the reorder point.

- **Order-Point, Order-Up-to-Level (s, S) system**
Continuous-review order system. As in the (s, Q) system, a replenishment is made whenever the inventory drops to or below s. However, contrary to the (s, Q) system, a variable replenishment quantity is used to raise the inventory position to the order-up-to-level S. The two systems are identical if the transactions are always unit sized and the order-up-to-level is equal to $S = s + Q$. If this system is used optimally, it is always better than the (s, Q) system in terms of total costs of replenishment, carrying inventory, and shortage. However, it requires more computational effort to find the best (s, S) pair. The disadvantage of the (s, S) system is the variable order quantity. As a result, suppliers or employees could make errors more frequently or costs are higher if quantities are not predetermined in terms of pallets of boxes. (s, Q) and (s, S) are equal if only one item is taken out of the inventory at the time.

- **Periodic-Review, Order-Up-to-Level (R, S) system**
Replenishment cycle system. This system is common use, particularly in companies without sophisticated computer control. Every R units of time, enough is ordered to raise the inventory above level S. Due to the periodic review, this system is much preferred when ordering from external suppliers or the distributor. For example, ordering a truck full of items is more efficient than with a few items. The (R, S) system offers a regular opportunity to adjust the order-up-to-level S, which is desirable if the demand pattern is changing with time. A disadvantage is that the replenishment quantities vary.

- **Periodic overview, Order-point, Order-Up-to-Level (R, s, S) System**
A combination of the (s, S) and (R, S) systems. Every R units of time, the inventory position is checked. If it is at or below the reorder point s, enough is ordered to raise it to S. (The (R, s, S) system as a periodic version of the (s, S) system. Also, the (R, S) situation can be viewed as a periodic implementation of (s, S) with $s = S - 1$.) Under quite general assumptions concerning the demand pattern and the cost factors involved, the (R, s, S) shows itself as the best system.

Inventory visibility

The replenishment logic described above is in Figure 4-8 directly linked to inventory visibility, because it is almost impossible to replenish the correct amount of items if the inventory levels are unknown. The replenishment logic is based on specific threshold values or order up to quantities. If the inventory is not visible and thus unknown or incorrect, the replenishment logic can not be executed properly. At the same time, if the inventory is visible, but there is no replenishment logic, nothing happens.

The main problem in retail stores is the lack of a correct inventory record, due to the limited inventory visibility. More information, in other words more visibility, can solve the problem. Assuming a reference situation, more information could range from counting the inventory one extra time up to total visibility and a live view of the inventory. Hence, more information is a vague definition and is more comprehensively explained in section 5-2.

Order restrictions

The level above inventory visibility and replenishment logic is order restrictions. Order restrictions are also store and situation dependent. Order restrictions could be in the form of a minimum order quantity, or maximum due to a lack of space. Examples of other order restrictions are: minimum or maximum value, specific order time, lead time, seasonal restrictions or rounding quantities.

4-2 Analysis of the problem

Almost all retail stores make use of an inventory system, to automatically replenish their inventory, to a specific extent. Therefore, almost all stores are dependent on an inventory system. In theory, this would not be a problem and a retail store can function correctly if it uses an inventory system as described that is based on accurate data. However, in a real store more elements have to be taken into account. One of the most important ones is that errors are made throughout the process, which result in errors in the inventory system. Simultaneously, there is a lack of information to compensate the errors by adjusting the system record. As a result, the replenishment is based on an inventory system with incorrect information. The result is over- or under-stocking. Over-stocking results in redundant inventory and under-stocking results in OoSs.

4-2-1 Errors and a lack of information

The inventory system as described in the previous section is a theoretical situation in which the different variables are known. In reality, more elements must be taken into account. The two most critical are errors made in the process and the lack of information to compensate those errors. Customers and employees are involved in the process. These make known and unknown errors. A few examples of errors that can be distinguished are [DeHoratius et al., 2008] [Merckx and Cassimon, 2016]:

- Theft

    Shoplifting by customers

    Internal theft by employees

- Human errors at the POS, during inventory audits and throughout the different process in the store

- Replenishment errors

- Incorrect (re-)hanging or labelling
- Lost or misplaced items

These errors result in an incorrect inventory record. In essence, the errors made are not the real problem regarding the replenishment. The problem is that the errors are not corrected in the inventory record, which results in an inaccurate inventory record.

4-2-2 Inventory record inaccuracy

In today's stores, most of the processes such as forecasting, ordering and in-store replenishment are based in the inventory record system. The problem is that as a result of the errors made, in time there will be a discrepancy between the retailers inventory records and the physical inventory available in the store. Hence, store processes are based on incorrect inventory data. This incorrect data is called Inventory Record Inaccuracy (IRI). IRI is defined as the discrepancy between the recorded inventory quantity and the actual inventory quantity physically available [DeHoratius et al., 2008].

Magnitude of IRI
Several studies have been done into the magnitude of IRI. Numbers that are found differ, however are significant. For example the study of [DeHoratius and Raman, 2008] found the IRI to be around 65% after examining nearly 370.000 inventory records from 37 stores of one retailer. It must be noted that these counts were performed at random times after the store was open for at least 2 years. Other studies found IRIs to be 51% [Kang and Gershwin, 2005] or 55% [Gruen and Corsten, 2007]. Although often cited, the problem with these scientific studies is that they are conducted for retail in general or for Fast Moving Consumer Goods (FMCGs). More recent studies that are focused on apparel present different numbers, they present an Inventory Record Accuracy (IRA) (instead of IRI) after a half year of about: 67,4% [Salmon, 2016], 65% [Joseph and Kaur, 2017] and 60% [Doyle, 2016]. The differences in percentages can have different causes. The first one is that there is a difference between products in retail stores in general and apparel retail stores, especially in quantity and value. The second one is how IRI is measured. To define the absolute error of one SKU the difference between the Actual Quantity (AQ) and Record Quantity (RQ) can be taken. However, with multiple SKUs, the IRI can be defined in different ways defined in [DeHoratius and Raman, 2008]

- With the use of 2 categories, accurate and inaccurate.
- With a threshold error, for example a specific value or percentage. (A record that is 1 off and has a total amount of 3 is 'more wrong', than a record that is 1 off and has a total amount of 1.000).
- With the use of a percentage of absolute size of the error divided by the AQ or divided by the RQ.
- With the percentage of the number of SKUs with a discrepancies between the AQ and RQ divided by the total number of SKUs.

Despite the difference in numbers, it is clear that there is on average not a high inventory accuracy. Inventory record accuracy is therefore often referred to as the missing link in retail execution [Heese, 2007].

In the rest of this research IRA, R_a, is defined with equation 4-3. Where Q_i is determined by the situations in which the actual quantity, Q_i^a, is equal to the recorded quantity, Q_i^r, for the total number of SKUs, n.

$$R_a(\%) = \frac{\sum_{i=1}^{N_{SKUs}} Q_i}{N_{SKUs}} \cdot 100, \qquad Q_i = \begin{cases} 1 & if \quad Q_i^a = Q_i^r \\ 0 & otherwise. \end{cases} \tag{4-3}$$

Consequently the IRI, R_i is defined with,

$$R_i(\%) = 100 - R_a(\%).$$

The error is defined as the difference between the RQ and the AQ. In reality, the error between the AQ and RQ can be positive or negative. Resulting in an overstated system inventory or an understated system inventory. If items are for example stolen, the actual inventory is lower than the recorded inventory. The recorded inventory is overstated. An overstated inventory record can result in OoSs. An understated inventory record can result in an excess inventory. The problem with an excess of inventory is the risk of not selling an item and the extra holding costs.

Practical example
Table 4-1 shows a practical example of the problem [Säilä, 2013]. The example shows two different t-shirts, T1 and T2. In the beginning, the inventory levels are correct and corresponding with the retailers needs. In the first count, two mistakes are made by a sales assistant. The sales assistant counts T2/S as a T1/S shirt and counts a T1/M as a T1/L shirt. The actual inventory is still equal to the required inventory levels. Then the replenishment takes place, T1/M and T2/S are replenished and there are now 4 discrepancies between the actual inventory and the record inventory (after replenishment).

If the original stock level is the wanted stock level by the retail store, the following problems arise:

- **T1/S** The RQ is 2 and the AQ is 1. If the retail store sells 1 shirt, the RQ assumes there is still 1 left. As a result, T1/S will not be replenished resulting in an OoS situation.
- **T1/M** The RQ is 1, the AQ is 2. As a result, the inventory system replenishes the item directly after it is sold. Resulting in unnecessary overstock.
- **T1/L** Similar result as SKU T1/S.
- **T2/S** Comparable to T1/M.

The example is based on a sales assistant who makes a mistake, similar results occur with other process mistakes or shrinkage takes place.

Table 4-1: Example of the problem that arises due to errors in the recorded inventory - based on source: RFID arena

SKU	Inventory level	After 1st count	Actual inventory	After replenishment	Actual inventory
T1/S	1	2	1	**2**	1
T1/M	1	0	1	1	**2**
T1/L	1	2	1	**2**	1
T2/S	2	1	2	2	**3**
T2/M	2	2	2	2	2
T2/L	2	2	2	2	2

The IRA of the example above can be determined with equation 4-3 and is equal to 33.3 %.

Despite several differences in product categories, industry findings suggest and studies find that the unknown inventory losses (backroom and sales floor shrinkage) are be a dominant drivers of IRI ([Kang and Gershwin, 2005],[Chuang and Oliva, 2015]). As a result, the most significant consequence of IRIs are overstated inventory records resulting in OoSs.

There are basically 3 ways to deal with an IRI:

- Eliminate errors. In practise it is often impossible to eliminate most of the errors. However, RFID could help reducing errors ([Fan et al., 2014], [Rekik et al., 2008]).
- Compensate errors. For example, if the mean of the loss rate each month is 5 lost items, the record inventory could be compensated with 5. However, the loss rate of each unique item is unknown and often too small to compensate regularly with a constant amount ([Kang and Gershwin, 2005], [Hardgrave et al., 2009a]).
- Manual counts more often to overwrite the inventory system. The problem with this solution in reality is that it is too expensive due to labour costs and that manual counting is also prone to errors [Kök and Shang, 2007]. However, with RFID, these counts can be executed much quicker. Studies show numbers ranging from 25 to 100 times as many items a minute with RFID compared to barcode scanning ([Hardgrave et al., 2009b], [GS1, 2014]). With overhead readers the inventory can be scanned continuously, without manual labour.

RFID enables more frequent counts, which can set the recorded inventory equal to the actual inventory. Thereby improving the inventory accuracy.

4-2-3 Out of stocks

An IRI is not the only factor that causes OoSs. Some other unexpected factors as a customer who comes in and buys an extraordinary amount of a specific SKU or sudden fashion trends can also result in OoS. However, these factors are assumed to be inescapable and only cause temporarily OoSs. Although percentages differ per study type and product type, an overstated record inventory is in the long term the main cause of OoSs. If an overstated inventory record is untreated it eventually results in a system that does not reorder a specific

SKU, because according to the recorded inventory the SKU is still available. The result is a so called replenishment freeze. This will result in permanent OoSs and thus extra revenue losses. This effect will result in higher losses than the initial inventory losses [Kang and Gershwin, 2005].

As explained in the previous chapter, different studies claim different percentages of OoSs in the range from 8% to 40%. The problem here is comparable to the IRI problem. There are major differences between retail in general, FMCG and apparel stores. Simultaneously, there are differences between different apparel categories. The most recent and relevant average percentage of OoSs is given in a major apparel retail survey [Salmon, 2016]. The study claims an average of 16.5%. It must be noted that the study only took major retailers into account.

Another problem comparable with IRI is the definition of OoSs. Some retailers see OoSs as the unavailability of items on sales floor shelves (shelf-OoSs), other only count OoSs if the product is unavailable in the total retail store (store-OoSs). Assuming that customers only buy items that are available on the sales floor, in the rest of the research OoSs are assumed to be sales floor OoSs. To determine the percentage of OoSs, the actual quantity for each individual SKU on the sales floor, Q_i^a, is determined, which results in $N_i = 0$ or $N_i = 1$, and the total number of SKUs, N_{SKUs}, is necessary. The percentage of OoSs is calculated with equation 4-4.

$$\text{OoS}s(\%) = \frac{\sum_{i=1}^{N_{SKUs}} N_i}{N_{SKUs}} \cdot 100, \qquad N_i = \begin{cases} 1 & if \quad Q_i^a = 0 \\ 0 & otherwise. \end{cases} \tag{4-4}$$

Despite the precise percentage of OoSs and the direct reaction of customers to OoSs, it has a significance influence on the retailer. The direct result for a retailer is lost sales and the indirect result is that the reputation of the brand name decreases [Thiesse and Buckel, 2015].

Average inventory
The average inventory is the sum of the inventory in the backroom and the inventory on the sales floor. It can be calculated with equation 4-2.

Lead time
The lead time is the time between the order and the actual delivery of items. In this time, the order is send to the Distribution Centre (DC), where items are picked and shipped to the store.

Inventory turnover rate
The inventory turnover rate is the rate in which the inventory is sold. It is calculated by dividing the sales by the average inventory.

Inventory losses
Inventory losses is the percentage of items that is lost or stolen. It is calculated by the number of lost items, divided by the number of lost items plus number of sales.

Number of customers
The number of customers that arrive in store in a specific time period. It is determined by the average arrival rate.

Customer demand
The number of products that customers want to purchase.

Conclusion

In this Chapter, the retail store is analysed as a system. The retail store is divided into a backroom and a sales floor, both with their own inventory which has to be replenished. The problem in retail stores is that the replenishment is based on automated inventory systems. However, these automated inventory systems are often based on an inaccurate inventory. This inventory accuracy is mainly caused by theft, internal theft as well as external theft. Due to the lack of information, it is unable to correct these errors frequently. An inaccurate inventory results in an increase in OoSs, since the inventory system thinks items are available, while they are not. With the use of RFID, a more frequent inventory count can be performed, which results in a higher inventory accuracy and thereby reduces the OoSs. The different RFID-deployments are discussed in the next chapter.

Chapter 5

The RFID-deployments

The following chapter explains the Radio Frequency IDentification (RFID)-deployments that are compared in this research.

This chapter answers the following research question:

What are the different RFID-deployments and to what extent can they obtain more information?

The chapter starts by explaining what information can be obtained in retail stores about the inventory. Where after a traditional retail store (used as reference) and the four RFID-deployments are explained.

5-1 RFID implementations in a retail store

The studies about RFID often study handheld RFID readers or translate RFID in general to a fully transparent store. However, there are many possibilities to implement RFID readers in a retail store. Several are given in Figure 5-1. All these different deployments result in different levels of information throughout the retail store. The level of information is determined by three parts, the accuracy of the obtained information, the frequency of obtained information and the accuracy of the location. A combination of RFID solutions inside the store will result in a particular level of information, a higher level of information will enable more accurate and sophisticated process improvements. However, randomly combining RFID solutions can result in a lacking system or unnecessary costs. This section will therefore explain the chosen RFID-deployments. In order to explain the deployments, first the levels of information are explained where after a reference situation of a retail store without RFID is presented.

5-2 Levels of information

The research determines what the impact of more information is on the Out of Stocks (OoSs) in an apparel retail store is. More information is a wide concept. This section explains

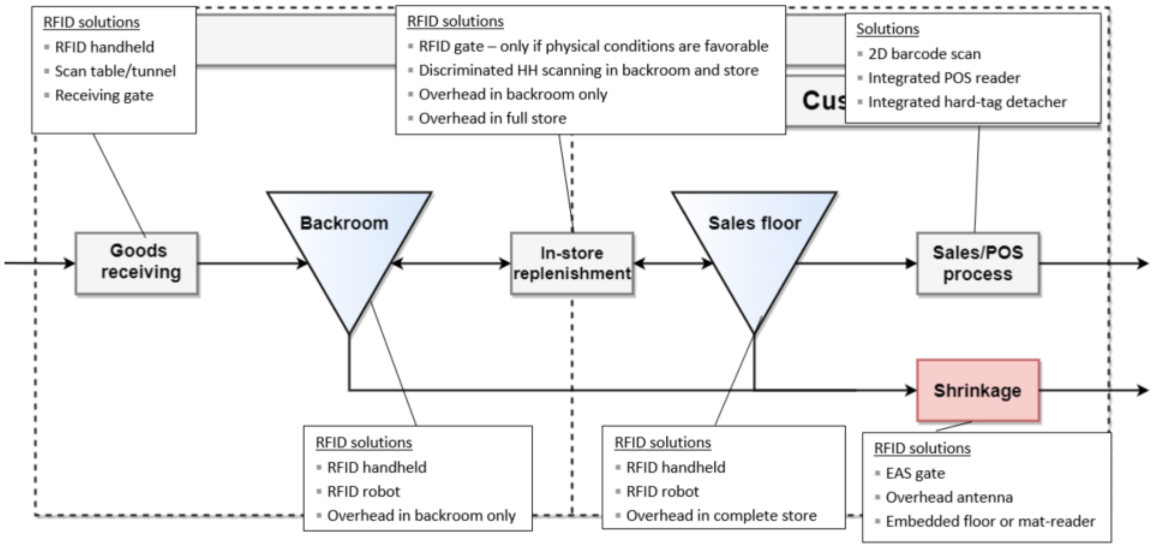

Figure 5-1: Several possibilities to scan the inventory at multiple points in a store

the different levels of information that can be obtained in a retail store regarding the Stock Keeping Units (SKUs). In traditional retails stores with barcodes, only the quantity of each SKU is determined. For example: 7 blue trousers of size 32/30. This information can be divided by adding the location, for example: 4 blue trousers of size 32/30 on the sales floor and 3 in the backroom. If a perfect inventory count is just performed, the quantity of each SKU is exactly known. However, over time due to the inventory losses, this accuracy deteriorates. With RFID, information can be obtained about each SKU individually.

The information for each group of SKUs or each item individually can be divided into the following three groups:

- **Frequency** As explained, the Inventory Record Accuracy (IRA) deteriorates over time due to inventory losses. If the inventory is counted, the recorded inventory is aligned with the actual inventory, resulting in a high inventory accuracy. Hence, the more frequent the inventory count is performed, the more accurate the inventory record. One of the key benefits of RFID is that these inventory counts can be performed a lot faster, thereby enabling the possibility of more frequent inventory counts. The increased frequency can range from an extra count a year up to live information about the inventory.
- **Accuracy** In the situation of a manual inventory count or a manual inventory count with bar-code scanners, errors as a double scan of the same product or skipping a product can be easily made. However, with RFID all the products are unique and multiple items can be scanned simultaneously. Double scanning is impossible and the change of missing an item is negligible. However, errors still can be made, for example incorrect labelling at the country of origin, tags that have fallen off or carelessness of employees scanning the inventory. Such potential human errors are discussed in [Chuang, 2015] and the influence of errors made by employees and the influence of full time employees on inventory accuracy are discussed in [Chuang and Oliva, 2015]. The

influence of sub-optimal read rates is discussed in [Thiesse and Buckel, 2015]. These errors are unique for each type of retail store and are influenced by many factors as employees, the quality of tags, the quality of the readers, density of tags and physical constraints. In this research all the inventory counts are assumed to be 100% accurate.

- **Location** Some stores see their stores as one inventory system and do not make a distinction between the backroom and the sales floor. These stores, mainly Fast Moving Consumer Goods (FMCGs) stores, rely their replenishment mainly on visual inventory checks. However, visually checking which sizes of blue trousers are sold out almost impossible unless each item is checked individually. By comparison, visually checking if a shelve with packs of sugar is empty is quite easy. The study of [Thiesse and Buckel, 2015] compares visual replenishment with RFID-replenishment. Due to the fact that RFID-tags have a unique identification number, in the situation of RFID a unique location can be added to each individual item. The accuracy of this location is determined by the different RFID-deployments. Where handheld readers can for example add a location as backroom or sales floor to each item and overhead readers can quite precisely determine its correct location within 1 meter. However, in the rest of this research it is assumed that the only locations added to items are backroom or sales floor. It is assumed that in every situation, including the reference situation with barcodes, the retail stores make a distinction between the backroom and the sales floor and that when items are moved from the backroom to the sales floor, their location is updated.

The focus of this research is on increasing the frequency of inventory counts. More information can be translated into a more frequent inventory count and thereby increasing the certainty about the correct quantities of each SKU. Enabling more accurate replenishment and thereby reducing the OoSs in theory. An example of this principle is shown in Figure 5-2.

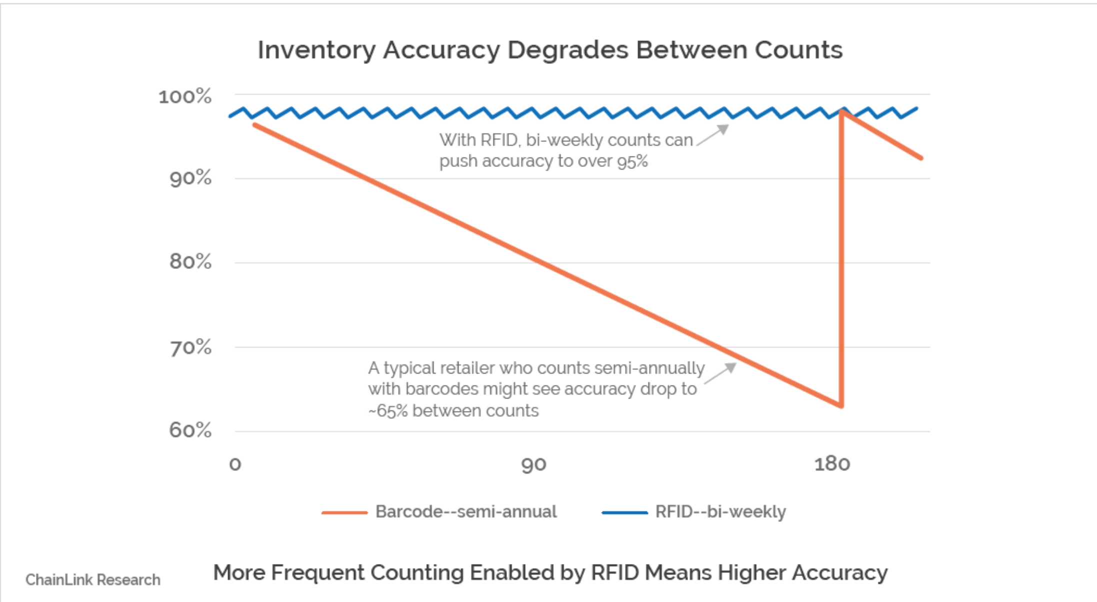

Figure 5-2: Example of the inventory accuracy deterioration over time - source: Chainlink

5-3 Tradition retail store

The original situation is based on the tradition retail stores that uses barcodes to identify their products, as most stores do. The retail stores typically have a backroom and a sales floor [Fisher, 2004]. Although some retail stores see their retail stores as one inventory system as described in section 4-1-1 and use visual inventory checks, apparel stores are less suitable for visual checks. It is therefore assumed that the original situation uses a distinction between the backroom and the sales floor and does not use visual checks.

Process of a traditional store
The original situation can be explained with the use of Figure 5-3. The physical item flows are presented by normal arrows and information flows are presented by dotted arrows. The level of inventory in the total store is based the physical flow of items arriving from the Distribution Centre (DC), the items that are sold through the Point Of Sale (POS) and shrinkage. The inventory system is updated by information from the DC, which presents the store a list of the items sent, updating the inventory system. The problem is that the received items can differ from the list of items given by the DC. However, these errors are left out for now. The other update of the inventory system takes place at the POS, that registers the items that are sold. The problem is the third flow: shrinkage. As described earlier, the inventory system is not updated by unknown errors such as shrinkage. As a result, the inventory accuracy deteriorates over time. To compensate the error between the actual inventory and the recorded inventory and often for accounting reasons, a manual count is performed once or twice a year [Merckx and Cassimon, 2016], which is represented by the manual overwrite. An inventory count is normally executed by an external company and is a labour intensive job. During an inventory count, the store is closed and each items is counted individually. Hence, there is no information about thefts, misplacement's and other irregularities throughout the period in between counts.

In order to compare the different RFID-deployments, a simplified version of this model is made with the following assumptions: no errors are made at the DC and POS. The inventory updates at those points are assumed to be always correct. Furthermore the replenishment from the backroom to the sales floor is based on the recorded inventory and if an item is moved from the backroom to the sales floor, the inventory system is updated. The difference between the RFID-deployments is the frequency of inventory counts.

5-4 Retail stores with RFID-deployments

To update the frequency of inventory counts, several RFID-deployments are selected in consultation with Mieloo & Alexander (MA), based on existing concepts and available technologies. In reality, deployments can slightly vary for specific stores due to the requirements of the retailer, aesthetic aspects or physical limitations. However, the principles are the same. The difference in the selected RFID-deployments is in this research limited to the frequency of the inventory counts. A critical requirement for RFID systems, is that items are tagged with RFID tags. There are many different tags and possibilities to tag items. Different authorities and companies developed tests and standards to measure the performance of specific tags on specific items. However, in this research it is assumed that all items are tagged correctly and that tagging errors do not occur.

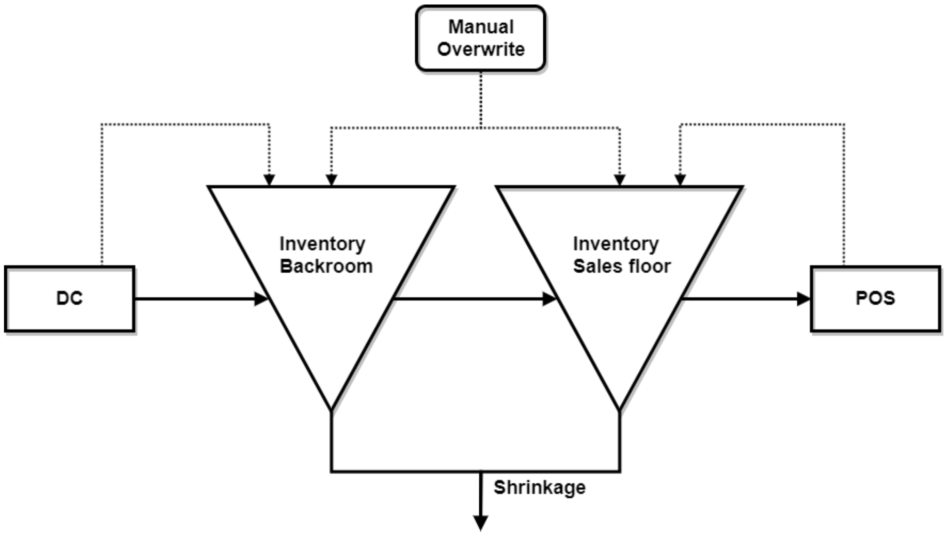

Figure 5-3: The inventory information process for a traditional retail store, deployment 1 and 2

5-4-1 Deployment 1 - A handheld reader

The first deployment is based on handheld readers only. This deployment is most frequently used and described in the literature. With the use of handheld readers, the process of manual overwriting the system inventory record with the actual record can be done more frequently, resulting in a higher inventory accuracy. Scanning items with a handheld reader makes it possible to scan many items at once, making the inventory count at least 25 times faster [Hardgrave et al., 2009a]. As a result, the inventory counts can be executed weekly instead of twice a year and the store does not have to close for a few days a year. Another important improvement in reality is that items can be directly scanned as they arrive. As a result, wrong deliveries can be noted and adjusted directly. Thereby, also improving the inventory accuracy. An example of the results of scanning more frequently on inventory accuracy is shown in Figure 5-2. In this example, the inventory accuracy deteriorates in a straight line over time. In reality, it is unknown which SKUs are lost in which rate over time and the deterioration is not a straight line.

5-4-2 Deployment 2 - A robot reader

In the second deployment, the human with a handheld reader is replaced by a RFID-robot. The RFID-robot can scan the retail store autonomously overnight. Increasing the scanning frequency and reducing the dependency on employees. In reality, a robot can scan a retail store multiple times over night at resulting in more constant, and therefore more accurate inventory scan compared to handheld readers. However, all scans are assumed to be 100% accurate.

5-4-3 Deployment 3 - Partially equipped with overhead readers, partially with handheld readers

In the third deployment, the store is partly equipped with overhead readers. Often the backroom is chosen to be equipped with overhead readers, the sales floor can be scanned with handheld readers. The backroom is often chosen for overhead readers because a) the concentration of items is higher in the backroom. Hence, more products are scanned per m^2 installation b) aesthetics do not matter in the backroom, c) stacked items in the backroom are harder to count manually. The system and obtained information is schematically shown in Figure 5-4. The grey area represents an area with 'real-time' information. Everything that is inside, enters or leaves this area is registered. Resulting that a directly inventory update in case of inventory losses.

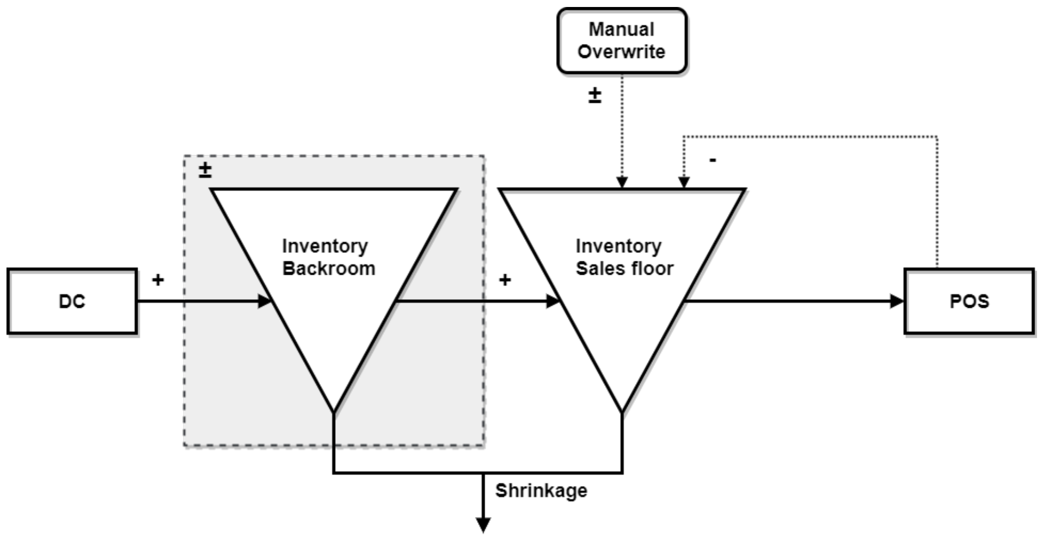

Figure 5-4: The inventory information process for deployment 3

5-4-4 Deployment 4 - Overhead readers

fourth deployment consists out of overhead readers throughout the whole store. Resulting in an 'live' inventory. The system and obtained information is schematically shown in Figure 5-5.

5-5 Comparison between the RFID-deployments

In practical applications, varieties can exist in the deployments itself and in the use of it. For example, larger stores could use a handheld reader only once every two weeks and smaller stores can scan their inventory daily. However, in this research, the deployments are used as described in this chapter. Only taking the frequency of inventory counts into account, a clear distinction between the difference RFID-deployments, which is visually presented with Figures 5-6 to 5-11.

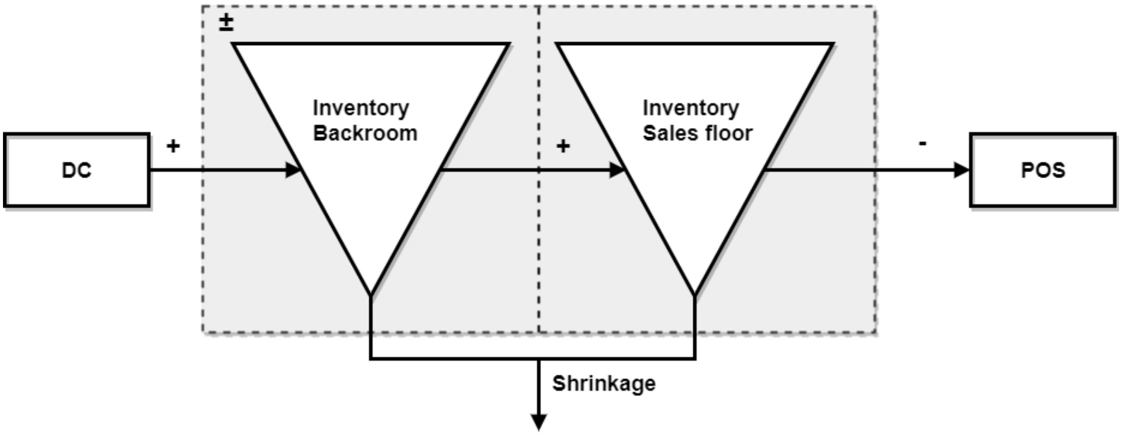

Figure 5-5: The inventory information process for deployment 4

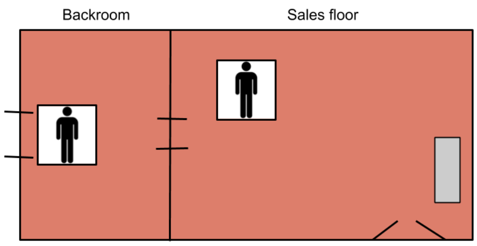

Figure 5-6: Original situation

Figure 5-7: Legend

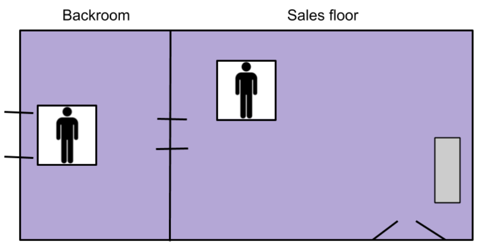

Figure 5-8: Deployment 1 - handheld readers

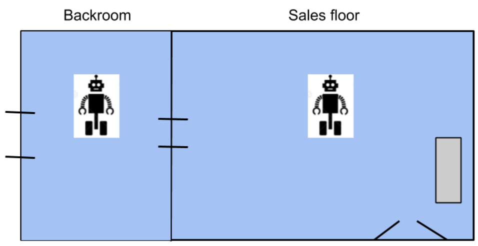

Figure 5-9: Deployment 2 - robot reader

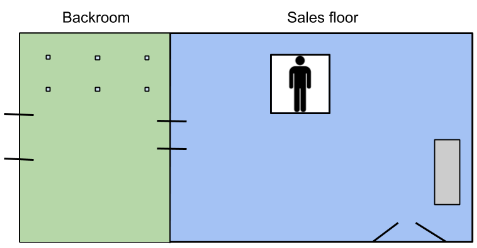

Figure 5-10: Deployment 3 - partially overhead, partially handheld

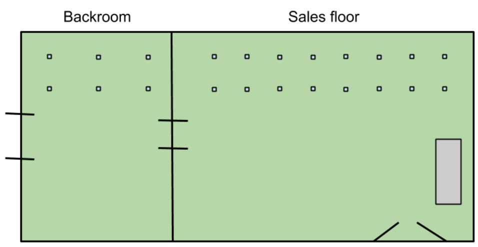

Figure 5-11: Deployment 4 - full overhead

Conclusion

RFID is a promising technique to obtain more information. The extra information obtained by RFID can be divided into: a higher frequency of obtained information, more accurate information and a more accurate location. The focus in this research is on increasing the frequency of inventory scans, thereby reducing the discrepancy between the actual inventory and the recorded inventory. A replenishment based on more accurate inventory data should result in less OoSs. The following RFID-deployments are compared in this research: handheld readers, a robot reader, partially overhead readers or a complete overhead system, resulting in inventory scans that are performed once a week, up to continuous, instead of twice a year in a traditional store.

Chapter 6

The base model

The following chapter presents the constructed base model. The base model is used as reference store from which the Radio Frequency IDentification (RFID)-deployments for different types of apparel store configurations can be compared.

This chapter answers the following research question:

What are the different types of apparel store configurations?

This chapter highlights prior conclusions from the literature including a preliminary analysis, to construct the model. The differences between a general retail store and an apparel retail, including the characteristics of the base model and describes the different store configurations that are compared.

6-1 Literature conclusions

To compare the different RFID-deployment described in the previous section for various apparel retail stores, a base model is constructed based on the literature. The conclusions from the literature to construct the base model of an apparel store are listed below:

- Most of the fundamental researches that use discrete event simulations to test specific parameters are limited to one Stock Keeping Unit (SKU) of a Fast Moving Consumer Good (FMCG), with an inventory quantity of about 50 and a daily demand of 10 ([Kang, 2004],[Agrawal and Sharda, 2011], [Thiesse et al., 2007], [Thiesse and Buckel, 2015]). Simultaneously, they assume an unlimited backroom or see the retail store as one entity. In this research, an apparel store with a higher number of SKUs is examined. The quantity of each SKU is significantly lower than with FMCG and the store is divided into a backroom and a sales floor, which are both limited and need replenishment. The SKUs only leave the store if they are purchased by customers or through inventory losses. The demand is based on the average inventory turnover.

- The pilot store studies ([Bottani et al., 2016], [Bertolini et al., 2012], [Hardgrave et al., 2013]) use specific store data. They prove that RFID can work. However, the results are less relevant for other store types, the data is not available and parameters can not be adjusted. It is therefore necessary to construct a generic store.

- RFID is often presented as potential solution. However, a comparison between different RFID-deployments is barely made. The study of [Agrawal and Sharda, 2011] tries to determine the optimal frequency of inventory alignment, because scanning with hand-held readers is still a labour intensive job. The study determines that alignment of the physical inventory with the recorded inventory more often than once a month is not worth the extra labour costs. However, with more advanced RFID-deployments, the argument of human labour omits. Furthermore, is the study limited to one inventory system with one product with a high quantity. It is therefore not representative for an apparel store.

- Different replenishments are used in retail stores, based on different replenishment logics. In this research, the replenishment logic (R,s,S) is used, where R can be varied depending on the store type and if the replenishment is to-store or in-store. R is one of the parameters varied. Setting it to zero will give the same replenishment logic as with the (s,S) logic, which is equal to (s,Q) if only 1 item is bought simultaneously. However, in reality customers can buy multiple at once. The order up to quantity is determined by the original inventory. The threshold value is determined by the average demand and lead time. Since, the demand is quite smal and lead time only 1 day, it is determined at 10%.

- The supply from the Distribution Centre (DC) is assumed to be unlimited for now. In reality, Out of Stocks (OoSs) can also occur in a DC. However, this is not taken into account in the base model.

- A retail store has, in reality, many SKUs with different selling rates, which can even have different replenishment strategies. These can even vary over time due to seasonal changes. However, this research focuses on the so called 'Never Out-of-Stock' items, which should be available throughout the year. All SKUs are assumed to be equal in terms of demand over time and their replenishment strategies.

- Inventory losses. As explained, errors made throughout the retail process can result in an under or overstated inventory record. It is assumed that there are only inventory losses, due to shrinkage which is accounted for the majority of errors [Kang and Gershwin, 2005], [Chuang and Oliva, 2015] and that shrinkage results in OoSs. The study of [Chuang and Oliva, 2015] finds that backroom shrinkage and shelf shrinkage are the dominant drivers of Inventory Record Inaccuracy (IRI). It concludes that under shelving along with erroneous data capture and checkout have negligible impact on IRI, compared to shrinkage. In other studies, the inventory losses are assumed to be between 1% - 7% [Kang and Gershwin, 2005] or 2% in backroom and 2% on sales floor [Chuang and Oliva, 2015]. For retail in general, the inventory shrinkage is often between 1.5% and 2%. However, high risk products as apparel is around 3%, the percentage for children clothing can even be higher [Bradford,]. The inventory losses assumed in this research are 1.5% in the backroom and 1.5% on the sales floor.

- Inventory turnover. The number of customers that arrive daily and the size of the inventory of a retail store are variable. What is more constant is the average inventory turnover for certain apparel categories. It can be calculated by dividing the sales in a year with the average inventory. In order to use a specific number, the average of three categories over a couple of years is calculated and shown in Table 6-1. With the assumption that all years and all categories have an equal share, the average inventory turnover per year is 3.2. This is however, somewhat lower than average inventory turnover found in different sources. Most of the found inventory turnovers in the apparel industry lie between 3 and 6. The base model store is open 7 days a week, instead of 5 or 6, and assuming that the economy is attracting, a inventory turnover of 5 is assumed.

  However, it must be noted that if the same source from Table 6-1 is used for supermarkets and grocery stores, an average of 14.7 is found. Similar results are found in [CSI,], where the retail industry average is 8.27, the apparel average 3.69 and the groceries 14.38. If we compare these results with some scientific literature studies, the values are quite low. Depending on the study and parameters, the inventory turnover ranges from 50 up to 140 (e.g. [Kang, 2004], [Agrawal and Sharda, 2011], [Condea et al., 2012]). Even if the lowest range of inventory turnover from scientific papers that use simulations is taken into account, it is about 3 times as high as the grocery store average and about 6 times as high as the retail average. However, these values are unrealistic and not taken into account, but a sensitivity analysis is performed for a higher inventory turnover.

Table 6-1: Inventory turnover per category - source: Retail Owner

Inventory turnover	2012	2013	2014	2015	2016	Average
Mens Clothing	2.4	2.3	2.5	2.8	2.6	2.5
Womens Clothing	3.6	4.2	3.8	3.4	5.4	4.1
Family Clothing	3.2	3.4	3.0	2.6	2.8	3.0
Average	3.1	3.3	3.1	2.9	3.6	3.2

Preliminary analysis

This research is focused on replenishment and item availability. Some retail concepts or items that do not make use of regular replenishment are not suitable regarding the base model. Although RFID can still help to identify what is available in-store, the replenishment based on accurate information is left out and the effect of reducing OoSs will thus be limited. To give examples, a discount store with or without a limited backroom that orders their inventory in bulk, supplies the inventory to their stores at once and that has the policy: while stock lasts or a limited edition seasonal clothing line that is not replenished. These stores often do not have a standardized inventory. Hence, if an item is sold out, it is removed from their inventory list and therefore not OoS. However, other uses of RFID could be applied to such stores. For example, if the stores have a higher inventory accuracy, they can lower the threshold value for their online sales. To give an example, retail stores try in growing numbers to combine their offline and online inventory or give customers the option to buy online and pick-up in store. Since retail stores often do not have an accurate inventory, they use high threshold values to offer some sort of certainty of available products to the customers. For example, 5 items. If this can be reduced to 2 or even 1, they can offer significantly more products online, that are available in-store. However, this application is not the focus of this research and is left out. The model is therefore only applicable to apparel stores that replenish there standard inventory regularly.

6-1-1 The constructed apparel base store

Although an apparel store is familiar to everyone and looks as a normal uncomplicated logistical process, there are many aspects included. Even if many factors are excluded, such as fashion trends, brand image, store lay-outs, customer emotions, irregularities of employees and other external factors there are still many elements that vary per store or situation making each retail store unique.

In order to be able to compare the different RFID-deployments and the effect on store configurations with specific parameters, a base apparel store is constructed. This store is a simplified version of a real apparel retail store, shown in Figure 6-1. This is necessary because it is otherwise unable to compare different effects for apparel stores in general, some values or factors are too variable, several are unknown or almost impossible to model.

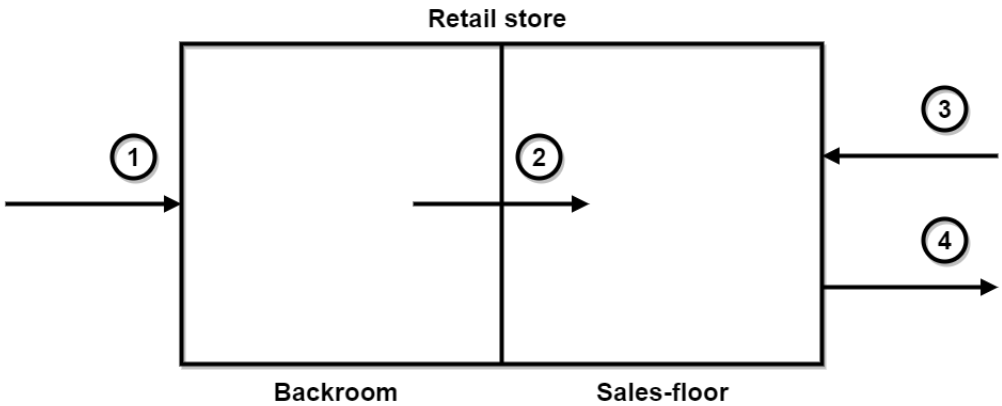

Figure 6-1: The basis for the constructed model

Differences between a general retail store and an apparel store The store contains a backroom, where items arrive. A sales floor which is replenished from the backroom and customers who enter the store and can purchase items. This design is quite generic.

The following characteristics or figures are included and chosen to model an apparel store and to distinguish it from a regular retail store:

- The nature of apparel makes it often impossible to do a quick visual inventory scan. For example, if the milk is sold out, it is seen directly. If blue trousers of brand X, wide model, in size 32/30 is sold out, it is almost impossible to notice between all other trousers. Visual inventory checks are therefore excluded.

- The average quantity of each SKU available is a lot lower compared to FMCG, simultaneously the inventory turnover is lower.
- Item level tagging can be used in apparel retail store because the prices of the products are higher than in grocers and because the products do not have the physical limitations that reduces read rates.
- OoSs are more important to apparel retailers compared to grocers because of the following reasons: a) substitution is limited, b) customers often come to a specific apparel store because of distinct clothes or services, where supermarkets are often chosen on the basis of its location and in general have similar products as their competitors, c) customers in apparel stores often buy in low quantities and leave if a product is not available. In supermarkets customer often have a basket full of products and do not leave the store if one product is unavailable, d) there is more competitive pressure.
- All other variables selected on the basis of the literature are in line with apparel stores and not with regular retail stores.

Determined variables for the apparel base model

The following values are determined for the apparel store which will be used as base model. Because of the fact that it is a simplified version of a real retail store, calibration of some values is necessary in Chapter 8.

Table 6-2: Characteristics for the apparel base store

What	Value	Explanation
P1: Quantity SKUs	250,6	Number of SKUs and average product quantity per SKU
P2: Replenishment	1w/1d	To-store once a week, in-store once a day
P3: SF/BR ratio	0.5/0.5	Ratio between sales floor and backroom
Inventory turnover	5	The inventory turnover per year
Inventory losses	1.5%/1.5%	Inventory losses on backroom and sales floor
Threshold inventory	10%	Based on average demand and lead time
Lead times	1d/-	To-store 1 day, in-store directly
Customer demand	(0,2)	Lower and uper limit of customer demand
Time in store	10	The time a customer is in the store in minutes

The first 3 variables are parameters that are varied in order to mimic different store configurations. Other variables that are assumed and that could influence the results of the model are tested in a sensitivity analysis.

The number of customers a year, N_c, number of SKUs, N_{SKU}, average quantity per SKU, q_{SKU}, the inventory turnover, i_t, average demand, d, are used to calculate the average inter-arrival time between customers λ with the equations below:

$$N_c = \frac{N_{SKUs} \cdot q_{SKU} \cdot i_t \cdot 0.6}{d}. \tag{6-1}$$

$$\lambda = \frac{365 \cdot 480}{N_c}. \tag{6-2}$$

Parameters to be varied

In order to compare the reduction in OoSs for different retail store configurations, 3 basic parameters are chosen to be varied to mimic different types of apparel retail stores.

- **Sales floor/backroom ratio**
  The ratio between the sales floor and the backroom can significantly differ in specific types of stores. In a discount store, the percentage of items on the sales floor is quite high, where in a shoe or exclusive store the majority will be stored in the backroom. The ratio of the base store is assumed to be 50%/50%. It is varied to 25%/75%, and 75%/25%.

- **Average number of items per SKUs** The average number of products is dependent on the story type. A more exclusive store with various sizes often has less items of a specific SKU than a discount store with only 3 sizes. The average number of items per SKU can vary roughly from 1 up to about 15. It is assumed that the average quantity of each SKU is 6, (ranging from 3 to 9). Which is varied to 3 (ranging from 1 to 5) and 12 (ranging from 8 to 16)

- **Replenishment frequency**
  The replenishment can be divided into the in-store replenishment frequency and to-store replenishment frequency. Store replenishments are dependent on various factors, such as if the location is close to the DC, size of the store and type of the store. It is assumed that to-store replenishment can vary between twice a month, weekly and once every 3 days and that in-store replenishment can be daily or once every hour. The standard replenishment frequencies are: to-store weekly and in-store daily.

KPIs

The RFID-deployments for the various apparel retail stores are compared regarding their reduction of OoS. The Key Performance Indicator (KPI) is the percentage of OoS on the sales floor. Calculated with the equation 6-3

$$\text{OoS}s(\%) = \frac{\sum_{i=1}^{N_{SKUs}} N_i}{N_{SKUs}} \cdot 100, \qquad N_i = \begin{cases} 1 & if \;\; Q_i^a = 0 \\ 0 & otherwise. \end{cases} \tag{6-3}$$

In reality, not every OoS leads directly to a lost sales. However, because of the fact that substitution factors are not taken into account, the percentage OoS can be linked to the number of lost sales.

The second KPI used to determine if the solution is viable, is the average inventory. A slightly increased average inventory and as a result, less OoSs is often acceptable. However, just doubling the inventory to reduce the number of OoSs slightly is not a solution, since extra inventory comes with extra costs and is not always physically possible.

The inventory accuracy is used as a tool to check the behaviour of the model. However, purely regarding this research and the reduction of OoSs it is not a KPI. The other performance indicators described earlier in Chapter 4 are kept constant.

The base model is implemented into the model in the next chapter and it is calibrated in Chapter 8.

Conclusion

The base model used to compare the RFID-deployments for various store types is described in this chapter. In reality, each retail store is unique and has its own characteristics. To compare several retail store types, the base model is created from which parameters can be adjusted. The different types of retail stores compared in this research are all based on the constructed base model. The following parameters are adjusted to mimic different store types: sales floor/backroom ratio, average quantity per SKU and the replenishment frequency. The adjusted parameters do not represent actual stores, but do mimic store types in order to get the results for a particular type of retail store.

Chapter 7

The simulation model

The following chapter translates the base model from the previous chapter into a simulation model.

This chapter answers the following research question:

How can the different RFID-deployments be compared for different store configurations?

It starts by explaining the relevance of a simulation as a decision support tool. The second part explains in steps how the simulation model is created and works with the use of flow charts and examples. The third part explains the implementation of the different Radio Frequency IDentification (RFID)-deployments and presents the complete implementation of the base model into the simulation model.

7-1 Approach

In order to compare the selected RFID-deployments and their influence on the system, a model is made. The model is used to run simulations. The most general definition of a simulation can be defined as [Robinson, 2004]: *An imitation of a system.* A simulation is often used to study different elements in a system or to analyse the influence of parameters on the system. The simulation can be static (a moment in time) or dynamic (behaviour over time). A simulation model is a simplification of the reality, because it is often unlikely that a simulation can represent reality in full detail. In other cases it is not desirable, since the time required to make and run the model would be excessive. A simulation predicts the performance of operations under a specific set of inputs, in contrary to other modelling approaches which attempt to provide optimum answers (e.g. linear programming) or near optimum answers (e.g. heuristic methods) [Robinson, 2004]. The model user can enter a scenario and the model predicts the outcome. It can therefore be used as a decision tool.

A simulation is often used, because of the natures of the system. For example a system that is subjected to variability. The variables can be predictable or unpredictable. The arrival of customers, their demands and inventory losses are for example unpredictable variations.

Systems are also often interconnected. Components do not work isolated and affect one another. The change of one, can lead to the change of another. It is often difficult to predict these effects, especially with variability [Robinson, 2004]. The advantages of a simulation versus experimentation with a real system are: less expensive to perform tests, less time consuming, control of the experimental conditions or the fact that the real system does not (yet) exist and a simulation can therefore be used to determine its performance.

A simulation is a suitable tool to compare the different RFID-deployments for various configurations of a retail store and is therefore used. A simulation can be applied in several ways, the most common used are:

- Static/Monte Carlo Simulation, a static simulation performed many times.
- Continuous Simulation, state is continuous and changes continuous over time.
- Discrete event Simulation, state is discrete and changes at a particular time point.
- Hybrid Simulation, a combination of a continuous and discrete event simulation.

An apparel retail store is a system, with discrete products and variable events in time. A static simulation is not suitable and a continuous simulation is not necessary. A hybrid simulation is only used in situations, where discrete events such as the arrival of a tanker and a continuous event as filling a tanker are combined. Because the changes in a retail store are discrete events in time, a discrete event simulation is used. However, before simulations can be run, the simulation model must be created.

Discrete event simulation

A discrete event simulation is characterised by discrete sequence of events over time that result in state changes. For example the arrival of a customer in the system (the store), can change the system from empty to occupied with one customer. If the customer buys an item and leaves, the state (inventory level) of the store is changed. All these events happen at specific points in time. A discrete event simulation jumps to the next scheduled event in time, instead of continuously calculating the state of the system for small time steps. A discrete event simulation usually starts with an initialisation, where the system state variables are initialised and the clock is set, it then runs a while or for loop and updates statistics until the end condition is met.

Python

The model is created in Python. Python is an open source, object-oriented programming language. Python supports modules and packages, which enable many functionalities. For example, the package SimPy, which is a process-based discrete-event simulation framework based on standard Python or Matplotlib, which enables visual plots.

7-2 The model explained in steps

To explain the different aspects of the model, it is divided into separate parts. To show the working principles of the model, arbitrary, sometimes exorbitant, values are used to give examples. The model is eventually used to run simulations. As explained, the simulations are discrete event simulations with time steps of 1, which is assumed to be equal to 1 minute. Each day contains 8 hours, equal to 480 minutes. The total simulation time, t_{end}, is determined in days.

7-2-1 A basic inventory model

The first step in creating the model is making a basic inventory model of an inventory system without losses. The actual inventory at the beginning of a period I_{k+1} is influenced by the inventory at the beginning of previous period, I_k, the received items due to replenishment a_k and items sold to customers e_k over the period. The relationship is given in equation 4-1.

Arrival and demand of customers

The rate in which items are sold is dependent on the arrival rate of customers, their demand and availability of items. The arrival of customers is based on inter-arrival times. The inter-arrival time is randomly picked from a Poisson distribution with λ as variable. The demand of customers, D, is created by randomly picking a variable from a discrete uniform distribution between a and b. It is assumed that if a customer wants an item and it is available, the customer buys it and if not, the customer does not buy it, neither a substitute. The inventory consists out of physical items. Therefore, it can never be negative.

Replenishment process

In order to provide a sufficient amount of inventory over time, replenishment is necessary. The inventory system is controlled by the (R, s, S) replenishment logic. Each review period, R, the current inventory is checked and compared to the threshold value s. If the inventory is below or equal to the threshold value, a replenishment order is made. The order arrives after the lead time, t_{lead}, and the inventory is then replenished up to S. In this example, only one type of Stock Keeping Units (SKUs) is used. However, this logic is applied to each SKU if the inventory system contains multiple SKUs.

The basic inventory model process

Figure 7-1 shows the process steps of a simple inventory model with one product type, including customers and a replenishment process. The process starts with an initialisation, where after the model runs until $t_{sim} \geq t_{end}$. During the simulation, the model handles the next customer and checks if $t_{sim} \geq R \cdot k$, where R is the review period and $k = 1, 2, 3, ...$ If this condition is true, the replenishment process starts, which only replenishes the store if the inventory is equal to or under the threshold value and sets the new k to the old $k + 1$.

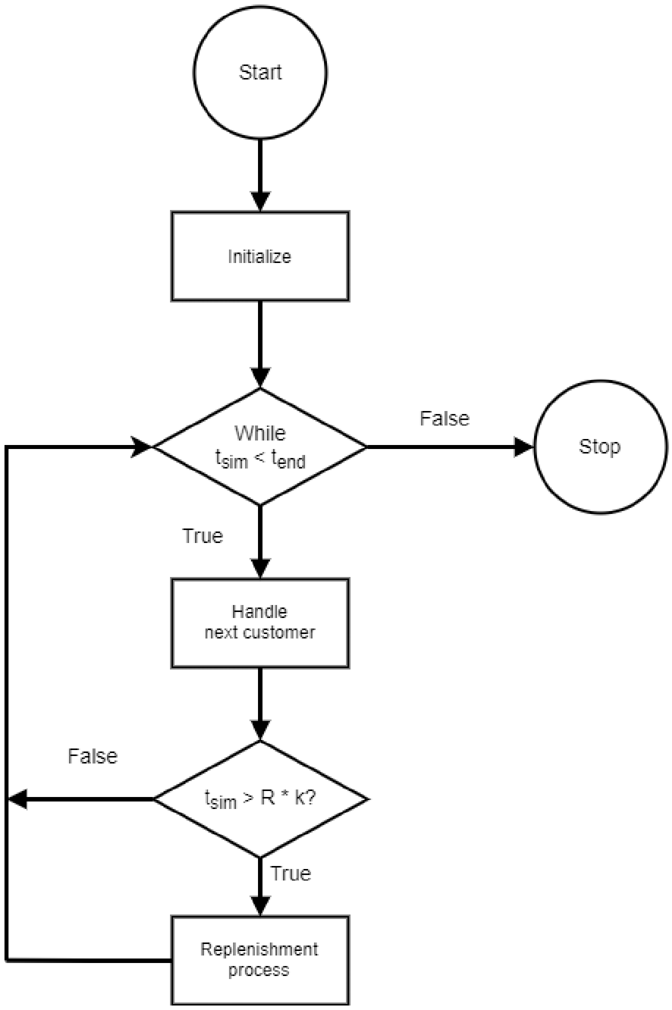

Figure 7-1: A flow chart of the store process with one inventory system

To explain the inventory systems works, two examples (Situation A and B) are given with the values from table 7-1 and 7-2. The results are shown in Figures 7-2 and 7-3. Figure 7-2 shows that the inventory is replenished after each day, because the inventory is below its threshold value at the the review period, R. In situation B, the inventory is only replenished after the second day, because after the first day the inventory is still above the threshold value.

Table 7-1: Example - variables basic inventory model

S	s	R	t_{lead}	t_{end}	(a, b)	Seed
100	10	1 day	0 days	3 days	(0,3)	123

Table 7-2: Example - variables inter-arrival times

	λ
Situation A	3
Situation B	8

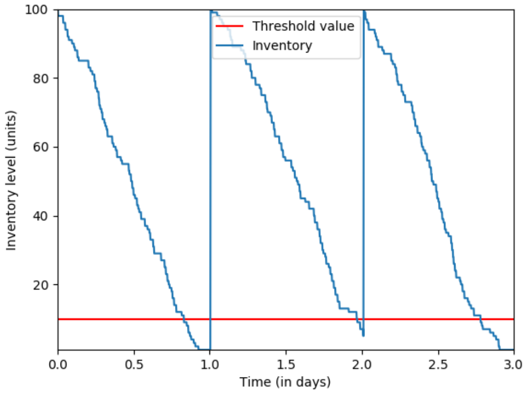

Figure 7-2: The inventory level over time - Situation A

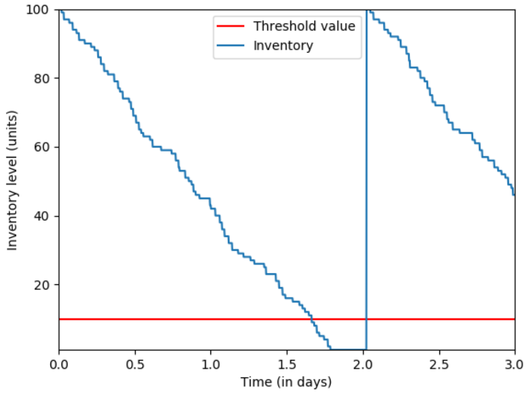

Figure 7-3: The inventory level over time - Situation B

7-2-2 Inventory losses

In the examples above, there are no inventory losses. However, inventory losses must be taken into account. Hence, a distinction has to be made between the recorded inventory and the actual inventory. Equation 4-1 is thus in reality the recorded inventory and not the actual inventory. The recorded inventory, $\tilde{I_{k+1}}$, is from this point given with the equation below:

$$\tilde{I_{k+1}} = \tilde{I_k} + a_k - e_k. \tag{7-1}$$

The actual inventory, I_{k+1}, where inventory losses, l_k, are included, is given with the following equation:

$$I_{k+1} = I_k + a_k - e_k - l_k. \tag{7-2}$$

To show the influence of inventory losses, l, given by a percentage of the demand over time, two examples are given. The variables added or changed compared to situation A in the previous example are given in Table 7-3.

Table 7-3: Example - variables basic inventory model with losses

Situation A			Situation B		
t_{end}	l	s	t_{end}	l	s
10 days	2%	50	40 days	2%	50

The result of situation A is shown in Figure 7-4. Initially, the recorded and actual inventory are equal. However, due to the inventory losses over time a distinction between the recorded and actual inventory arises.

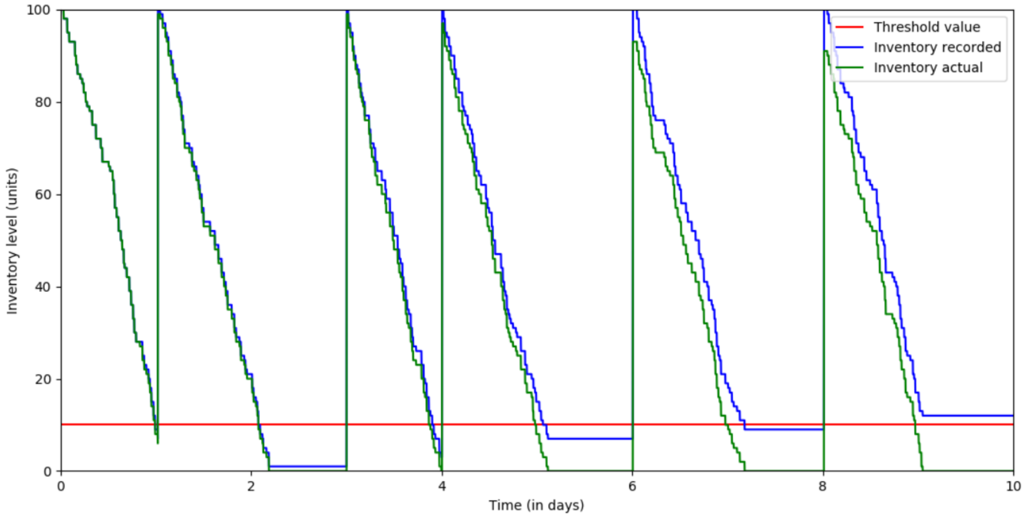

Figure 7-4: Example of the inventory over time in situation A

The result of situation B is shown in Figure 7-5. The example shows more clearly that the actual and recorded inventory diverge from each other over time. What can be seen is that over time the actual inventory curve hits zero more frequently and longer, resulting in temporary Out of Stocks (OoSs). Where after eventually, a permanent replenishment freeze occurs, with permanent OoSs.

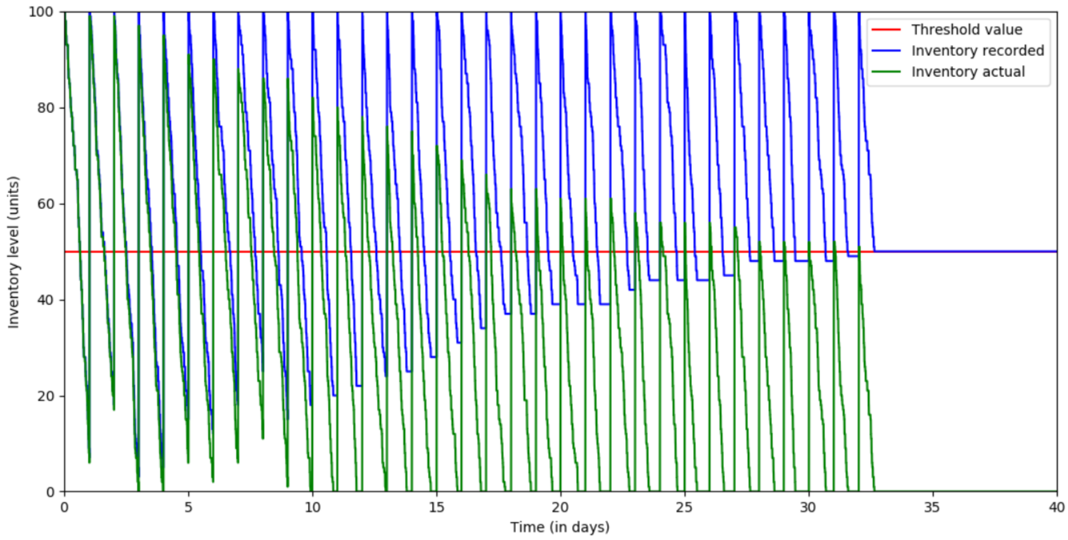

Figure 7-5: Example of the inventory over time in situation B

As a counter measure for the temporary OoSs and replenishment freezes, retailers often count their inventory once or twice a year. The frequency in which this happens is given in R_3. During an inventory count, the recorded inventory is set equal to the actual inventory ($\forall\ i, \quad Q_i^r := Q_i^a$). An example with a manual inventory count after 40 days is given in Figure 7-6.

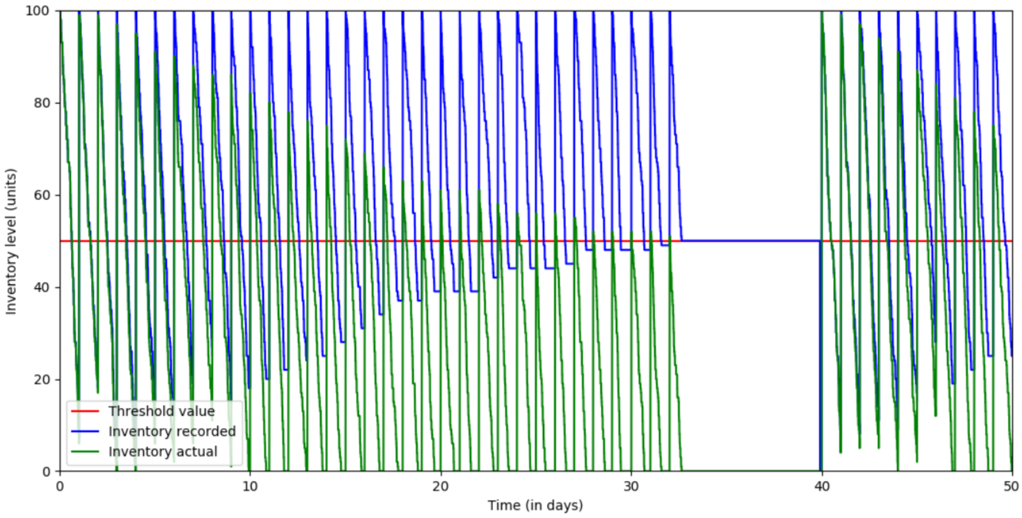

Figure 7-6: Example of the inventory over time in situation B, including an inventory count

7-2-3 Distinction between the backroom and sales floor

Retail stores exist out of a backroom and a sales floor. They can be seen as two inventory systems. Customers can only pick up items from the sales floor and the sales floor is replenished from the backroom. The store itself is replenished at the backroom, which happens less frequent than the replenishment of the sales floor.

The extended process is shown in Figure 7-7. The main differences with the process of Figure 7-1 are that the total inventory is divided between the backroom inventory, $I_{k,br}$, and sales floor inventory, $I_{k,sf}$, in the initialisation and that there is a in-store replenishment process and to-store replenishment process. The replenishments are triggered by review periods R_1 and R_2.

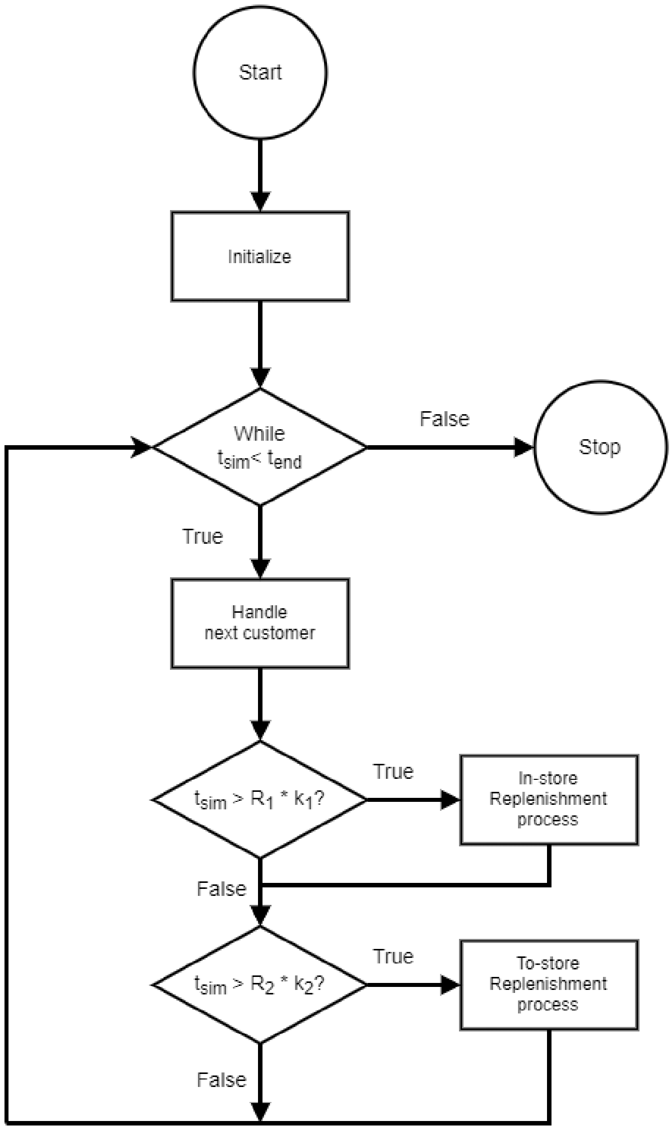

Figure 7-7: A flow chart of the store process with a backroom and a sales floor

To show an example, the values in Table 7-4 are used. The inventory losses only occur on the sales floor.

Table 7-4: Example - variables inventory model with a backroom and a sales floor

$I_{k,t}$	$I_{k,sf}$	$I_{k,br}$	s_t	s_{sf}	t_{end}	λ	R_1	R_2	l	Seed
500	350	150	125	40	80 days	12	1 day	7 days	2%	123

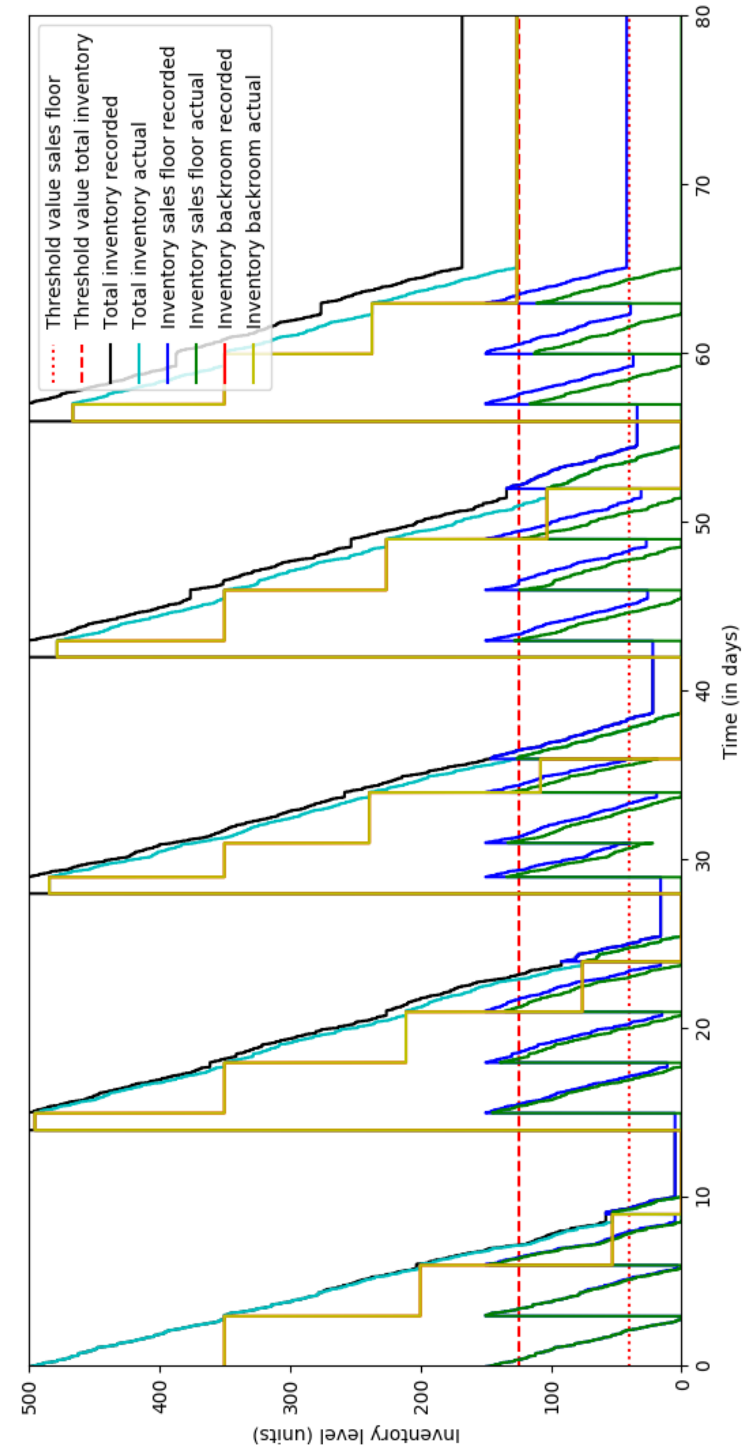

Figure 7-8: Example of the inventory of the total store, the backroom and the sales floor

In the example is the inventory system of the sales floor comparable to the previous examples. The sales floor is replenished from the backroom after each day. As a result, there is not a 'continuous' decrease of inventory in the backroom, but a discontinuous decrease in steps. In this example, there are no inventory loss in the backroom. The replenishment freeze therefore only occurs on the sales floor. However, in reality it can arise to-store as well as in-store.

7-2-4 The inventory

To show the basics of the model, an inventory of one product with a quantity between 100 and 500 was used. In reality, an apparel retail store has many different SKUs in lower quantities. A more realistic input has to be created. To give an example: 250 SKUs, with an average quantity of 10.

The first step in creating the starting inventory is the creation of a list with all SKUs, including the total quantity by randomly picking a variable from a discrete uniform distribution between a and b, in this situation 5 and 16. (similar as the distribution of demand, values are picked between 5 and 15, excluding 16). An example is shown in Table 7-5.

Table 7-5: An example of a created item list including corresponding quantities

SKU	Total_quantity
Item_1	10
Item_2	5
Item_3	15
...	...
Item_n	12

The next step is dividing the inventory between the sales floor and backroom according to the sales floor/backroom ratio $r_{sf/br}$. If this ratio is for example 0.4/0.6, then 40% of the items for each SKU are stored on the sales floor and 60% in the backroom during the initialisation. After is determined what part has to be added to the sales floor inventory, the rest forms the backroom inventory. The second step in creating the inventory is using the threshold percentage. The threshold percentage is used to determine if new items have to be ordered.

The quantity of each SKUs on the sales floor has to be at least 1. If there is a product quantity of 2 and the sales floor backroom ratio is only 20%, it is rounded up to 1. The rest is rounded in a regular way. As a result, the ratio of items on the sales floor can be slightly higher than the input ratio when using lower quantities of items.

To give an example a $r_{sf/br}$ of 0.4/0.6 and a threshold percentage of 20% used. The results are shown in Table 7-6.

Table 7-6: Example of the created inventory including threshold values

SKU	Total_quantity	SF_quantity	BR_quantity	Total_threshold	SF_threshold
Item_1	10	4	6	2	1
Item_2	5	2	3	1	0
Item_3	15	6	9	3	1
...	...	...	...	...	...
Item_n	12	5	7	3	1

7-2-5 Lead time, inventory losses, customer demand and observations

The following factors are relevant for the model, however assumed to be constant.

Lead times

It is assumed that each store is supplied from a warehouse with an unlimited inventory. However, products that are ordered have to be picked and delivered to the store. It is assumed that this process takes 1 day. Furthermore is assumed that the in-store processes are executed at closing time in the end of the day and are thus executed directly with no lead time.

Inventory losses

In the examples above, a constant inventory loss rate of 2 % of the total sales is used. To represent the inventory loss more realistic, the inventory loss also has to be generated random. Therefore, in stead of a constant inventory loss of 2 %, there is a chance of 1.5 % that inventory loss occurs, both on the sales floor and in the backroom. The magnitude of the inventory loss is determined similar to that of the demand of customers. *

Customer demand

The customer demand is determined by randomly picking the a value of 0,1,2 out of a uniform distribution. The result is an average customer demand of 1. If a customer is unable to buy the product he wants, he does not buy a substitution and in the situation where the demand is 2, the customer purchases the second one (if available), irrespective to the fact that the previous item was available or unavailable.

Observations

To monitor the variables during the simulations, observations are done. The observations of the recorded as well as actual inventories are done each 5 time-steps. The inventory accuracy and percentage of OoSs are observed before each in-store replenishment. Both are calculated with the formulas given in Chapter 4 and are used to plot the visualisations.

7-2-6 Model output

To explain the different examples, graphical outputs were used. However, to show the results of the complete model and to calibrate, verify and validate the model, two types of outputs are created. Graphical outputs and numerical outputs. Graphical outputs are overviews, which give an insight into the behaviour of the inventories, the percentage of inventory accuracy and OoSs over time. Examples are shown in Figure 7-10 and 7-11, after the implementation of the model.

Numerical outputs are used to compare the results for many simulation runs. For example the average percentage of OoS situations, when varying a parameter. An example is given in Table 7-7.

Table 7-7: Output example - the OoS percentages for variations of parameter 1

	p_1^1	p_1^2	p_1^3	..	p_1^n
Original situation	30 %	28 %	20 %	..	10 %
Deployment 1 - handheld readers	20 %	17 %	16 %	..	5 %
Deployment 2 - robot reader	18 %	16 %	14 %	..	2 %
Deployment 3 - partially overhead/handheld	16 %	10 %	8 %	..	1 %
Deployment 4 - full overhead	13 %	7 %	6 %	..	1 %

However, other data can also be relevant. Especially, because a specific output is based on the different parameters settings. To analyse the results, the parameter settings must be known. All the data is exported to a .csv file after each simulation. From here, the data can be used for an analysis.

7-3 Implementation of the RFID-deployments

A distinction between the backroom and sales floor is made in the model. It is assumed that the model contains two inventory systems which can be combined for the total inventory. The to-store as well as the in-store replenishment are both based on the recorded inventory. Hence, the replenishment is purely based on the recorded sales, which are assumed to be 100% accurate. In combination with the assumption that every inventory count is 100% accurate, the only difference between the RFID-deployments is the frequency of inventory counts, R_3. The frequency of the inventory counts performed by the different RFID-deployments are shown in Table 7-8. Each inventory count, the recorded inventory is set equal to the actual inventory.

Table 7-8: Frequency inventory counts

	Count frequency BR	Count frequency SF
Original situation	182 days	182 days
Deployment 1 - handheld readers	7 days	7 days
Deployment 2 - robot reader	1 day	1 day
Deployment 3 - partially overhead/handheld	Continuous	1 day
Deployment 4 - full overhead	Continuous	Continuous

The update frequencies of deployment 3 and deployment 4 are (partly) continuous. Continuous is modelled by the model as once every 5 time-steps.

All the RFID-deployments are implemented in the same model. A RFID-deployment must be selected before running a simulation. The RFID-deployments can thus be compared by comparing the results of different simulation runs.

7-4 Implementation of the base store

This section describes the implementation of the model, it combines the previously described elements into one model. The total model is based on the base model and corresponding values described in Chapter 6-1-1. A flow chart of the complete process, including inventory count is shown in Figure 7-9. Where R_3 is the frequency of the inventory count.

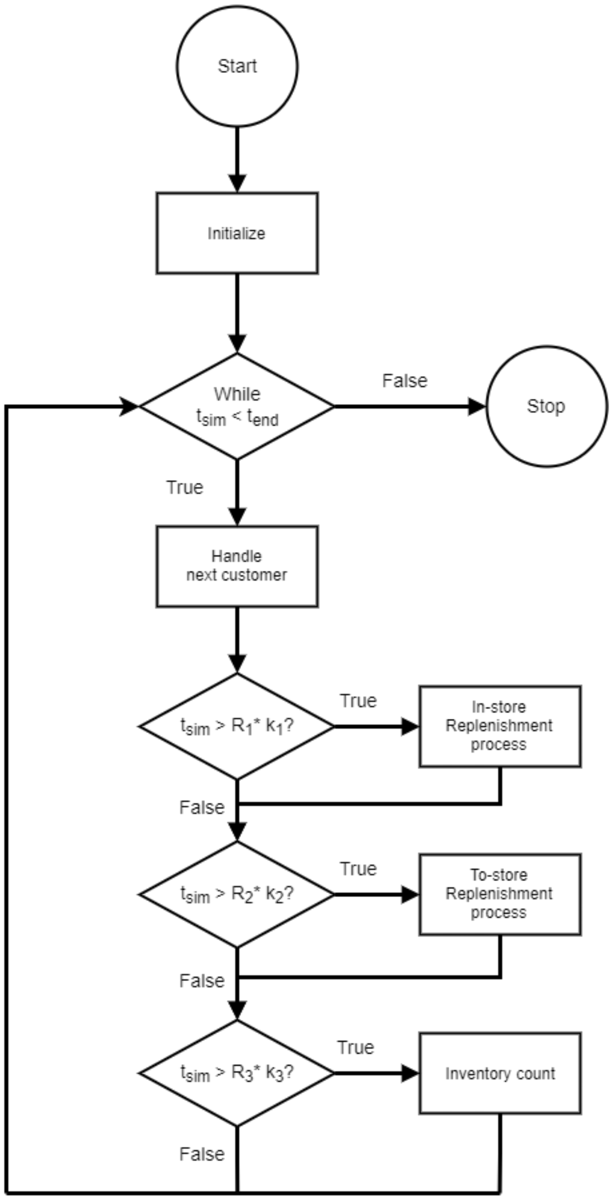

Figure 7-9: A flow chart of the complete process

The data determined for the base model in the previous chapter is implemented into the model. Furthermore is the option added to select the original situation or an RFID-deployment, t_{end} is 365 days and the seed is 1234 for the given example results.

However, some other variables are added, which have to be set before running the simulation:

7-4-1 Example results

Examples of the graphical outputs of the model for the original situation are shown in Figure 7-10 and 7-11.

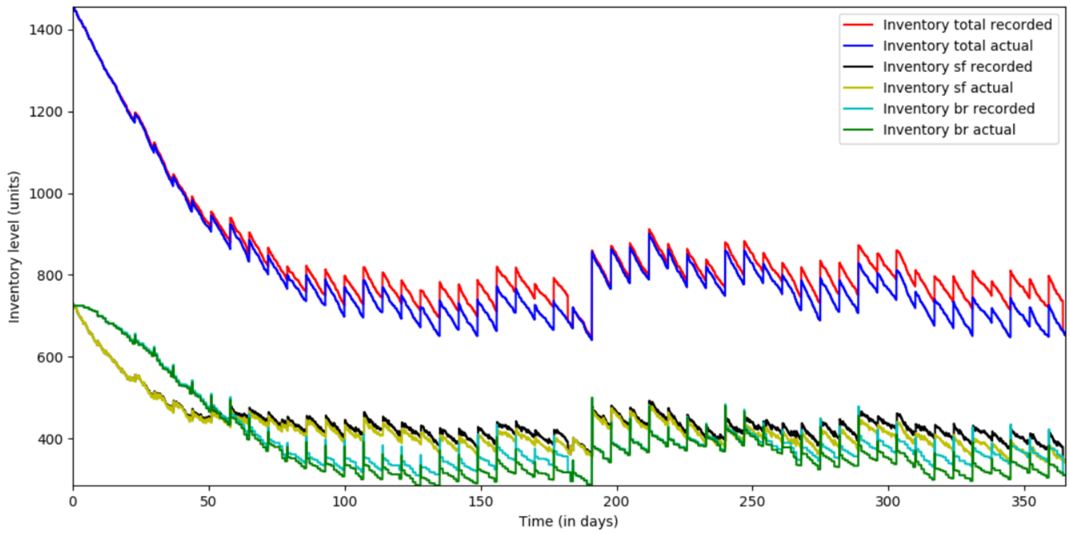

Figure 7-10: Example of the inventories levels over time

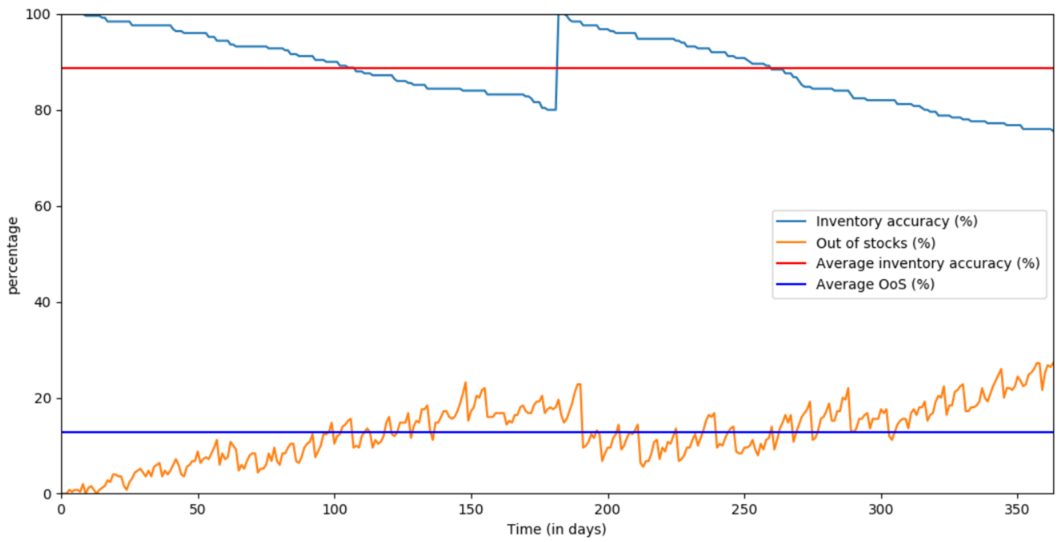

Figure 7-11: Example of the percentages of inventory accuracy and OoSs over time

In Figure 7-10 can be seen that the original inventory is higher than the average inventory, because over time new products are ordered at various moments. As a result, the original inventory will not be met again. What can be seen is that there is an increasing discrepancy between the recorded and actual inventory records up till the moment where the inventory is manually counted ($t_{sim} = 182 days$). Comparable results are seen in Figure 7-11. The inventory accuracy deteriorates over time until the inventory is counted. Simultaneously, the OoSs increase over time. These are plausible results. What must be noted is that the inventory is on average quite high in the first 50 days. This can influence the percentage of OoSs and must be taken into account in the next chapter.

Conclusion

The chapter describes the relevance of a simulation model in order to compare different situations and the influence of specific parameters without having to construct a real system. The model created is a discrete event model, which is used to run discrete event simulations. The second part describes how the theory is translated into a simulation model including the implementation of the different RFID-deployments, which can be selected before a simulation run starts. The chapter ends with an implementation of the base model described in Chapter 5. In the implemented base model, parameters can adjusted to compare the RFID-deployments for different store configurations.

Chapter 8

Experiments

The following chapter explains the experiments and presents the results of the experiments.

This chapter answers the following research question:

To what extent do the RFID-deployments reduce the number of OoSs for the different experiments?

The chapter starts with discussing the experimental plan among with the hypotheses. The next steps are determining the steady state, number of runs, calibrating the model and performing the verification and validation. Where after the experiments can be executed. The end of the chapter presents the results of the experiments.

8-1 Experimental plan

To answer the research question, results must be obtained and compared. Therefore, several experiments are performed. Experiments are carried out to support, refute or validate a hypothesis. The basic situation in each experiment is the implemented base model, from which several store types are mimicked.

The experimental plan contains the following steps:

- Setting up the hypotheses
- Calibration of the model, including:
  - Initialisation
  - Number of runs
  - Iterative calibration process
- Verification and validation of the model, including:
  - Verification tests

Sensitivity analysis

Validation

- Performing experiments
- Presenting the results

8-1-1 Hypotheses

The following hypotheses are made about the results regarding Radio Frequency IDentification (RFID) in general and about the specific experiments:

- In general is expected that for all experiments RFID will significantly reduce the number of Out of Stocks (OoSs) compared to the original situation. Furthermore is expected that the RFID-deployments relative to each other differ significantly less than compared to a situation without RFID. This is probably caused by the low inventory turnover, in combination with the daily and weekly replenishment. Hence, a higher deployment will probably has the most benefits, if other parameters are also adjusted. For example more frequent replenishment.
- Ratio sales floor/backroom: It is expected that the smaller the sales floor compared to the total store, the higher the OoSs. This is based on the fact that an equal amount of products is available in the total store. A smaller percentage on the sales floor results in a smaller buffer and faster replenishment freezes. A more frequent inventory count with RFID, should have more effects for stores with a smaller sales floor compared to stores with a larger one.
- Number of items per Stock Keeping Unit (SKU): It is expected that a higher number of SKUs results in a lower percentage of OoSs, because of the fact that the number of products is higher and therefore a higher buffer is available. It is expected that a higher RFID-deployment is more useful for lower quantities than with higher quantities per SKU.
- Replenishment frequency: It is expected that the replenishment frequency is one of the causes of temporary OoSs. Increasing the replenishment frequency should, therefore, reduce the number of OoSs. Hence, a frequent inventory count by a high level RFID-deployment is probably more useful for a high replenishment frequency, than for a low replenishment frequency. A combination of a frequent replenishment and a high level of RFID-deployment probably presents the lowest OoS percentage.
- Regarding the sensitivity analysis, it is expected that variables as inventory losses, inventory turnover, threshold values have significant influence on the OoS percentages. The inventory losses are the main cause for replenishment freezes, increasing the percentage will increase the percentage of OoSs significantly. Similarly, increasing the inventory turnover would also increase inventory losses up till the inventory is counted. Resulting in a higher percentage of OoSs. Increasing the threshold value, and thereby increasing the safety stock should reduce the number of OoSs.

8-2 Model calibration

The first analysis is to check if the model matches the 'reality' in general. Because the model is based on a constructed store, the results found in the literature are used to check if the model matches 'reality'. Model calibration is the process of adjusting variables of the base model within acceptable margins so that its matches the area being studied. Prior to calibration of the model, the initialisation period and the number of runs must be determined.

8-2-1 Initialisation period

In the situation of opening a new store, the store is completely filled. Over time, items are sold, stolen and replenished, eventually arriving in an operational state, often called steady state. The same accounts for the model, which has an initialisation phase and a steady state phase, in which data can be collected. This effect is shown in Figure 8-1. In the first period, the inventory is on average higher than the average over a longer period. If the data from the initialisation phase is included in in calculating results, it could lead to biased results.

It should therefore be checked if a higher inventory during the initialisation period influences the percentage of OoSs. For this test, the results over the total time period ($T_0 + T_E$) are compared with the results of only the second period (T_E) as shown in Figure 8-2. T_0 is determined to be exactly halfway the simulation period, directly after an inventory count.

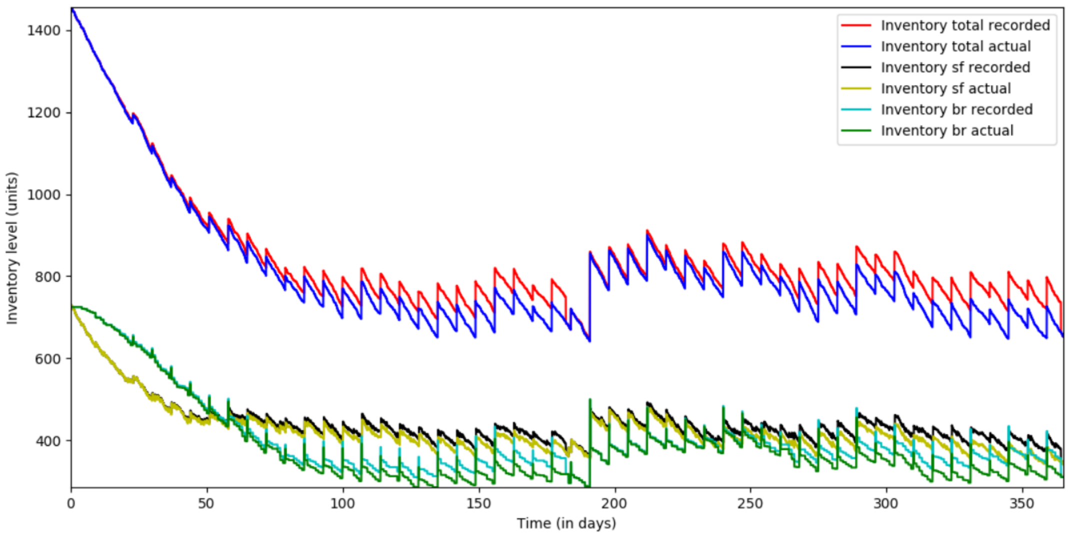

Figure 8-1: The different inventory levels over time

The tests are performed for a total period of 1, 2 and 4 years. The results are shown in Table 8-1. The percentage of the second half of the time-line is slightly higher than in the first half for the simulation of 1 and 4 years. However, a simulation of 2 years presents a different result. Multiple runs must be performed for more accurate results in order to determine the steady state period. It must be noted that these test are performed with a full store as starting inventory. Additional tests starting with an empty and a half filled store present similar results if measured over T_E only.

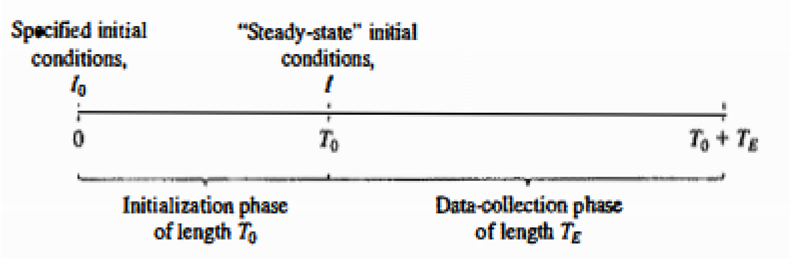

Figure 8-2: The initialisation phase - source: Discrete-event system simulation by J. Banks et al.

Table 8-1: The OoS percentages for different simulation times

	1 year	2 years	4 years
$T_0 + T_E$	11.47%	11.31%	11.68%
T_E	12.26%	11.18%	12.04%

8-2-2 Number of runs

Due to the fact that the model contains stochastic variables, variations in results can occur. A general principle is that more accurate statements can be made if more measurements are performed [Dekking, 2005]. The number of runs are therefore determined with equation 8-1 from [Dekking, 2005]. In this equation is n the number of runs, $z_{\frac{\alpha}{2}}$ is the critical value of the confidence interval, σ is the standard deviation and w is the width of the confidence interval.

$$n \geq \left(\frac{2 \cdot z_{\frac{\alpha}{2}} \cdot \sigma}{w} \right)^2 . \tag{8-1}$$

A confidence interval of 95% is chosen, resulting in a critical value of $z_{0.025} = 1.96$. Furthermore a width $w = 0.5$ is chosen. To calculate the standard deviation, 50 and 100 runs are performed for the simulation time of 1, 2 and 4 years. The results are shown in the Table 8-2.

Table 8-2: Average OoS percentages and standard deviations of 50 and 100 runs for 1,2 and 4 years

		50 runs			100 runs		
		1 year	2 years	4 years	1 years	2 years	4 years
$T_0 + T_E$	Avg. OoS	10.74%	11.11%	11.26%	10.88%	11.12%	11.34%
	St. dev.	1.06	0.86	0.63	1.04	0.83	0.69
T_E	Avg. OoS	11.39%	11.42%	11.28%	11.46%	11.58%	11.42%
	St. dev.	1.73	1.06	0.87	1.51	1.07	0.92

The average OoS percentage increases if the simulation time is set longer and the measurements are performed over the complete time ($T_0 + T_E$). This effect is not seen if the measurements are only performed over time T_E. It can therefore be concluded that the first period influences the percentage of OoSs. Furthermore can be seen that the standard deviation significantly reduces between performing the simulation 1 or 2 years. This effect is limited when the simulation time is increased from 2 to 4 years.

It is determined to measure only the steady state (T_E) of the simulation in combination with a simulation time of 2 years, because it forms the best balance between a low standard deviation and computational time. Filling in the highest standard deviation of a simulation of 2 year in equation 8-1 gives the following results:

$$n \geq \left(\frac{2 \cdot 1.96 \cdot 1.074}{0.5}\right)^2,$$

$$n \geq 70.9.$$

The determined number of runs should be at least 71. To increase margins each configuration is simulated 100 times.

8-2-3 Calibration of the model

The model is a simplified representation of reality. Some factors and processes are simplified or left out, furthermore assumptions are made. These factors can influence the results. Model calibration is normally achieved by an iterative process of comparing an revising. In each revision available variables can be adjusted in order to change how the model behaves, operates and simulates the process.

In this research, the model framework is based on a literature study. The model should therefore be compared to the literature instead of a the real system. Currently, the percentage of OoSs as output of the model is about 5% lower than the given average of the biggest apparel retails given in [Salmon, 2016]. The variables that are directly based on the literature can not be adjusted, however, the assumptions made throughout the research can be adjusted.

Various reasons can be pointed out for the discrepancy, which can mainly be divided into two categories: simplifications made, and assumptions made. Examples are: the fact that only inventory losses are taken into account and an understated inventory that is left out, explains why the inventory accuracy is on average higher than described in the literature. However, inventory accuracy is not the Key Performance Indicator (KPI) regarding the experimental results. The model is calibrated on the basis of the percentage of OoSs. Elements that are left out, which can influence the OoSs are: human errors, misplacements, incorrect arrivals and imperfect read rates. Furthermore, assumptions as a lead time of 1 day are done in the report. These factors are adjusted to calibrate the model.

Initial model
The tests below are all performed 100 times. As starting point is the simulation before calibration 100 times executed, the result is an average OoS percentage of 11.29%.

First revision: Lead time
The lead time is assumed to be 1 day. A lead time of 1 day is, however, quite optimistic, it is more realistic to assume 1 day for picking and preparing the order, and 1 day for shipping the order to store. The lead time is set to 2 days. Increasing the lead time from 1 to 2 days result in an average OoS percentage of 11.88%.

Second revision: Inventory turnover
After running the first experiments, it seems that the inventory turnover rate is too low.

The factor that calculated the average inventory from the starting inventory is adjusted from 0.6 to 0.64 (equation 6-1). The inventory turnover is now more in line with the determined number 5. A recalculation of the inventory turnover, which results in an inventory turnover close to 5 results in an average OoS percentage of 12.86%.

Third revision: Delivery of goods
It was assumed that the Distribution Centre (DC) has an unlimited supply and all the deliveries were 100% accurate. However, the DC does not have an unlimited inventory and errors are made such as wrong deliveries or wrong label tagging. Furthermore, human errors are made in-store and at the Point Of Sale (POS). To take all of these into account, it is assumed that in 10 % of the deliveries, the deliveries are wrong and are not added to the inventory. Adding an error chance of 10% to the deliveries results in an average average OoS percentage of 13.40%.

Fourth revision: Accuracy of the locations, scanning the inventory and other irregularities
The accuracy of the locations and scanning of products is assumed to be 100% in the report and other irregularities in the store are not taken into account. These could influence the OoSs and can therefore partly clarify the lower percentage of OoSs. These causes are not implemented in the model. However, the model still can be calibrated by adjusting another variable: the threshold value. The threshold value is based on the average demand, lead time and safety stock. It should at least cover the demand during the lead time. However, because of the fact that the inventory turnover in the apparel industry is quite low and the lead time is relatively short, the replenishment value can be quite low. It is determined at 10%. In the apparel industry, the number of products per SKU is often quite low. The rounding of the threshold value can have significant influence on the results. In the previous examples, the number is rounded regularly. A method of calibrating the model and compensating the location, imperfect scanning and other unknown factors is by rounding the threshold values down. This results in an average OoS percentage of 16.19%.

Fifth revision: Inventory turnover
After the third and fourth calibration, it seems that the inventory turnover rate is too high. It is therefore calibrated to 0.62, to ensure a inventory turnover in line with 5. The new OoS percentage is: 15.06%.

Although it slightly differs from the 16.5% found in the survey of [Salmon, 2016], it is assumed to be best obtainable for the model. In reality, there are always unexpected events and errors occur, especially in an environment where humans are part of the process. Other factors that are not included such as competition, location, weather influences, seasonal and weekly fluctuations are not taken into account. The remaining differences is assumed to be caused by unknown factors, which can not be modelled or compensated. This result will occur in all simulations, and the results can therefore still be compared to the base model.

All the adjustments form from this point the new base model. Since, the different factors can vary per store configuration, a sensitivity analysis about the calibration is made, with as reference the new base model. This sensitivity analysis can be found in Appendix B-6.

Recalculation of number of runs
Due to the calibration, the number of runs should be recalculated. Performing 100 of runs, with a duration of 2 years gives an average OoS of 14.96 % with a standard deviation of 1.163.

Filling these values into equation 8-1 gives the following results:

$$n \geq \left(\frac{2 \cdot 1.96 \cdot 1.163}{0.5}\right)^2,$$

$$n \geq 83.14.$$

The conclusion is that running each simulation configuration 100 times gives accurate enough results.

8-3 Verification and validation

In order to use the simulation results to construct conclusions, it is important to verify and validate the model. Models are approximate imitations of real-world systems and they never exactly imitate the real-world system. Therefore, a model should be verified and validated to the degree needed for the model's intended purpose or application [Sargent, 2005]. In this research, the intended purpose is to get an insight into the impact of different RFID-deployments on the OoSs for various store configurations.

8-3-1 Verification

In order to verify if the model is implemented correctly, verification is necessary. Model verification is often defined as: "ensuring that the computer program of the computerised model and its implementations are correct" [Sargent, 2005]. In other words, verification is answering the question: is the model right? Model verification is achieved by comparing the output of the model with what is expected from the input data, which can be done in several ways.

This section verifies the complete model in two ways. The first method is performing tests on a single simulation in order to verify the effects mainly graphically. For example: extreme values. The framework for performing a verification is: describing the situation, the test data, the expectation and output of the model (all tests are performed with random seed = 1). The second method is by performing a sensitivity analysis. In which 100 runs are performed for each adjustment of a variable in order to determine the influence of a specific variable.

Verification 1 - inventory losses

The first verification is testing if the model behaves according to the expectation regarding the inventory losses.

Situation
The main problem that causes permanent OoSs is an increasing discrepancy between the recorded inventory and the actual inventory, due to inventory losses. Hence, with inventory losses, over time the inventory accuracy should deteriorate and the OoSs should increase, up till the moment that an inventory count is performed.

Test data

- Test 1: base model with inventory losses of 1.5% in the backroom and sales floor.
- Test 2: base model without inventory losses.

Expectation

It is expected that, in the simulation with inventory losses, the inventory accuracy will deteriorate over time and that the percentage of OoSs will increase up till the moment that an inventory count is performed. This effect should not occur in the simulation without inventory losses. The simulation should only contain temporarily OoSs that fluctuate around a certain percentage.

Output of the model

The results are shown in Figure 8-3 and 8-4. As expected in test 1 with inventory losses, the percentage of OoSs increases over time and is corrected after each inventory count. Simultaneously, the inventory accuracy deteriorates over time and is also corrected at each inventory count. Test 2 does not show a decrease in inventory accuracy over time and shows a more constant percentage of OoSs. The variations in OoSs are caused by the replenishment frequency and random customer demands. What is interesting to notice is that there is a natural lower limit of the OoSs in the base model. What the influence of various elements, such as replenishment frequencies and inventory turnover rate is on these temporary OoSs is studied in the sensitivity analysis and the experiments. According to verification 1, the model behaves as expected.

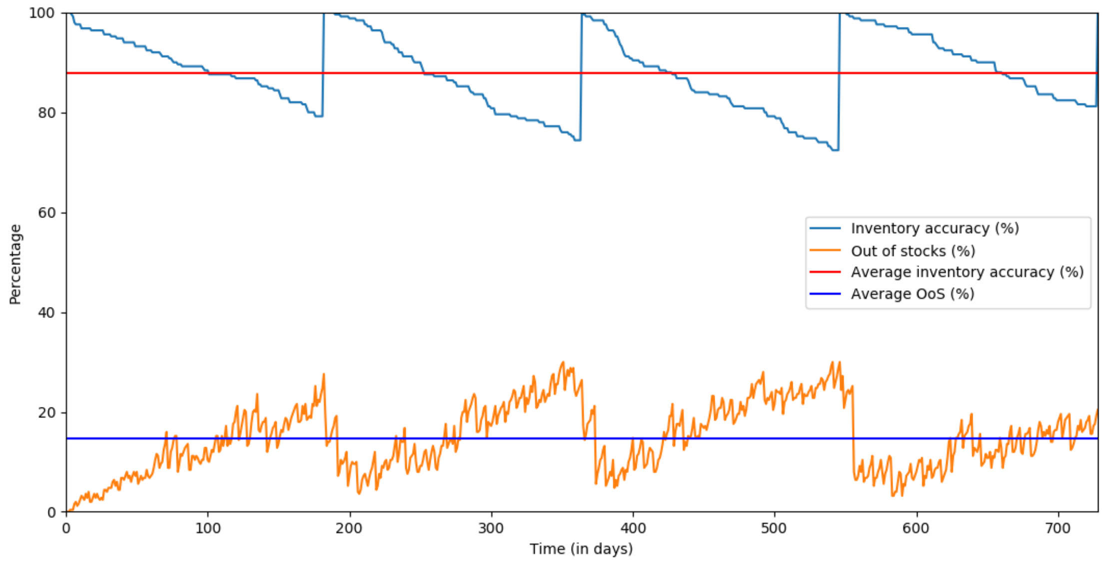

Figure 8-3: The inventory accuracy and OoS percentage over time - verification 1, test 1 with inventory losses

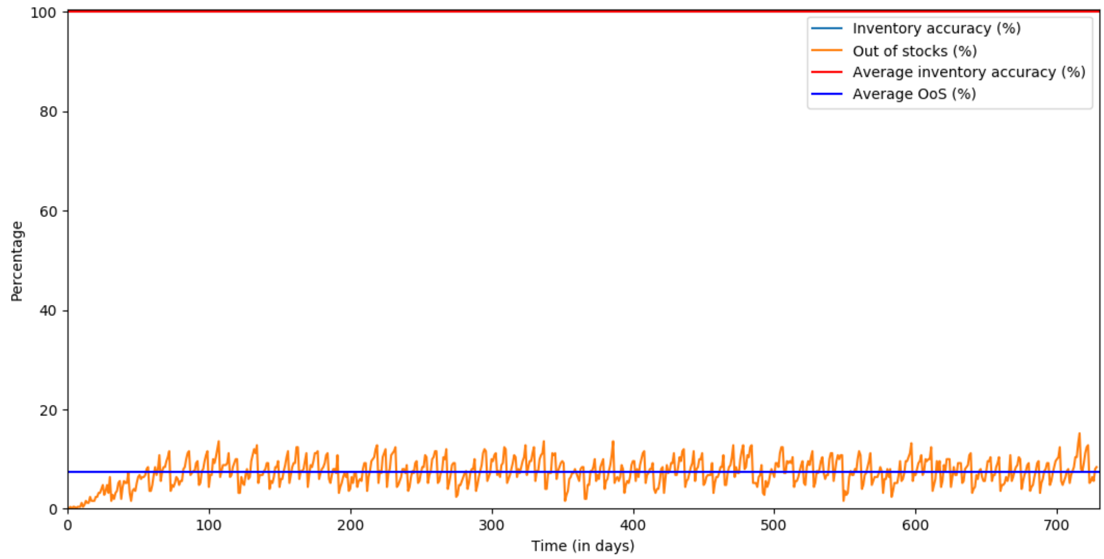

Figure 8-4: The inventory accuracy and OoS percentage over time - verification 1, test 2 without inventory losses

Verification 2 - extreme values

The second verification is testing if the model behaves according to the expectation regarding extreme values.

Situation
In the standard situation, customers arrive over time by an inter-arrival time determined by a Poisson distribution, based on the average inventory, customer demand and inventory turnover. In this situation, two extremes are tested. The situation in which only 1 customer arrives each day, and the situation where a customer arrives each minute. Furthermore, the average number of customers is store is measured.

Test data
- Test 1: inter-arrival time is 1 day.
- Test 2: inter-arrival time is 1 minute.

Expectation
It is expected that when only 1 customer arrives every day, almost nothing is sold. Hence, the average inventory accuracy should be quite high and the OoSs quite low. In the second test, where customers arrive each minute, it is expected that directly after a replenishment, most of the inventory is sold within days. Although this selling rate deteriorates over time up till the next replenishment. High values of inventory inaccuracies and OoSs are expected. Furthermore, customer stay 10 minutes inside the store, hence the average number of customers should be around 0.02 and 10.

Output of the model
The outputs can be found in Figures 8-5, 8-6, 8-7 and 8-8. As expected, with 1 customer a day the inventory decreases slowly over time and almost no OoSs occur. With 1 customer

a minute, the inventory directly lowers and the OoS percentages skyrocket directly and are close to 100 %. Over time, the discrepancies between the recorded inventories and the actual inventories are becoming increasingly clear. The OoS in Figure 8-8 starts around 30 % after just one day, this is caused by the fact that the inventory accuracy and OoS percentage is only calculated at the end of each day. The average number of customers in store in test 1 is 0.021 and in test 2 is 9.995. Hence, these values match with the expected values, as do the results of the tests.

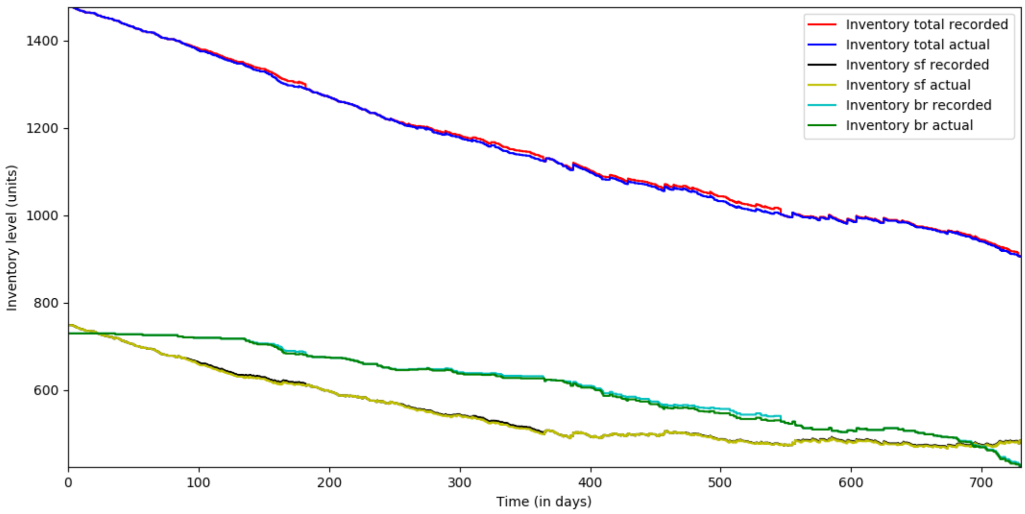

Figure 8-5: The inventory over time - verification 2, test 1 with only 1 customer a day

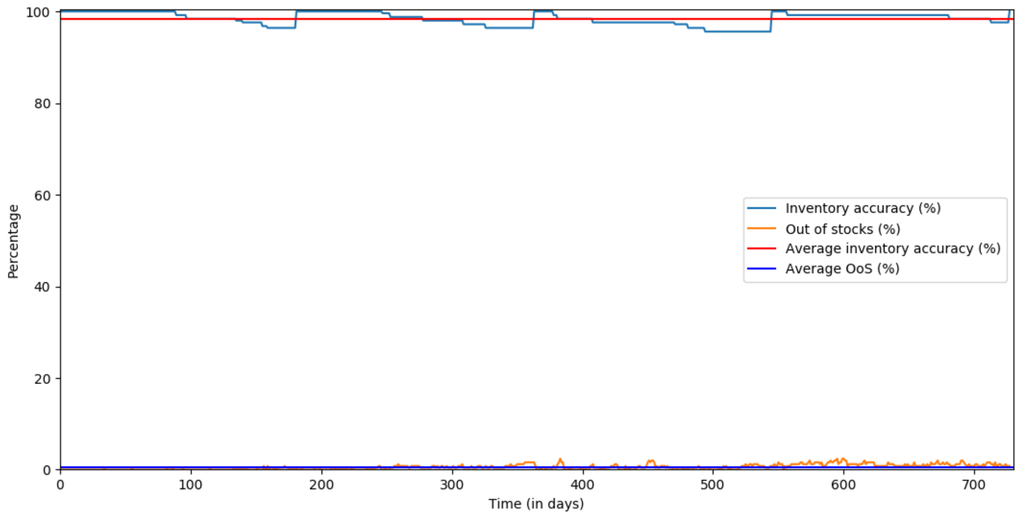

Figure 8-6: The inventory accuracy and OoS percentage over time - verification 2, test 1 with only 1 customer a day

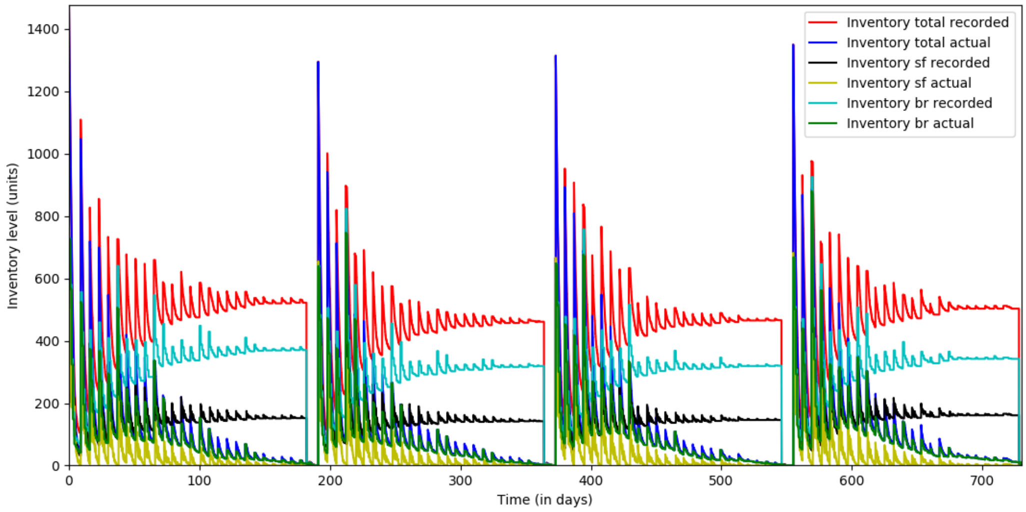

Figure 8-7: The inventory over time - verification 2, test 2 with 1 customer a minute

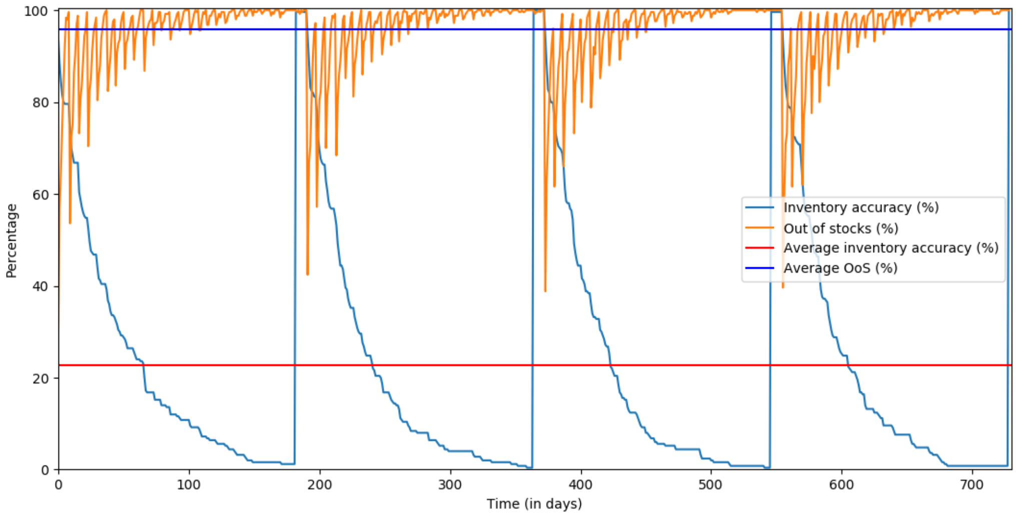

Figure 8-8: The inventory accuracy and OoS percentage over time - verification 2, test 2 with 1 customer a minute

Verification 3 - tracking of products

The third verification is testing if the model behaves according to the expectation regarding the tracking of two SKUs.

Situation

The model contains 250 SKUs, which are all products with their own quantities. The total number is divided between the sales floor and the backroom. The products are randomly sold from the sales floor in quantities of 1 at the time. No strange or negative values should occur.

Test data

- Test 1: tracking a single product (SKU 1).

- Test 2: tracking a single product (SKU 2).

Expectation

It is expected that single products should behave similar to all products together. However, because single products are checked, the total quantity is quite low and because absolute quantities are used, the tracking lines should be less continuous than the tracking of the total inventory. Furthermore, the backroom and sales floor quantities together should always represent the total quantity. The sales floor quantities should decrease more constant (one product at the time) compared to the backroom quantities, where after the replenishment threshold is met, multiple items are replenished. Similar, the total inventory should decrease gradually and be replenished all at once.

Output of the model

The outputs are given in Figure 8-9 up to 8-14. The figures behave according to the expectation. Where the backroom and sales floor combined form the total inventory. The shape of the lines of the total quantities are similar to the sales floor values.

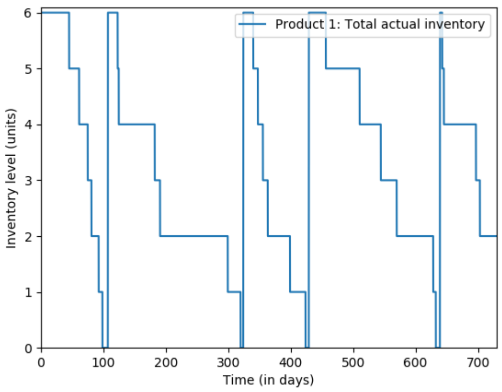

Figure 8-9: Total inventory over time SKU 1

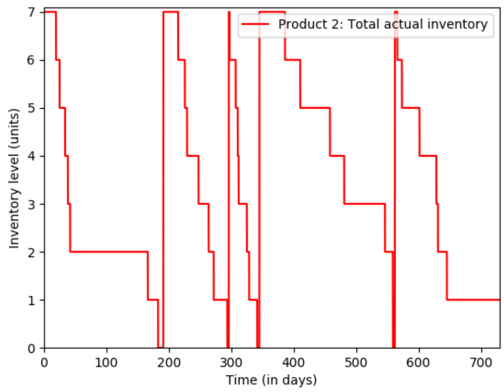

Figure 8-10: Total inventory over time SKU 2

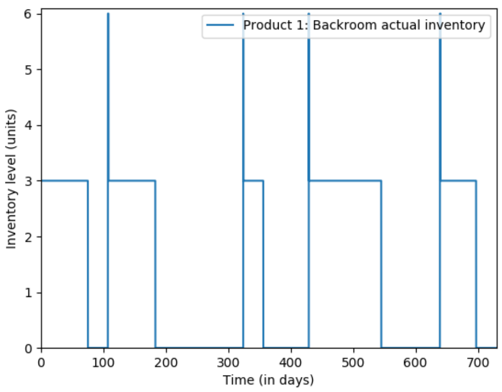

Figure 8-11: Backroom inventory over time SKU 1

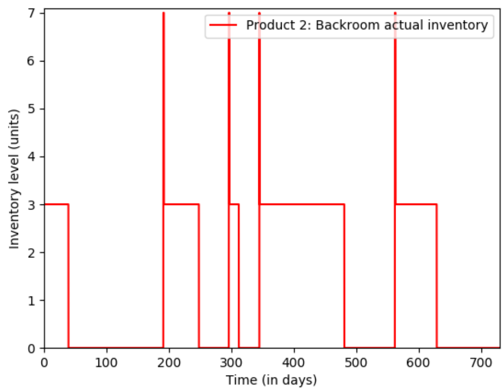

Figure 8-12: Backroom inventory over time SKU 2

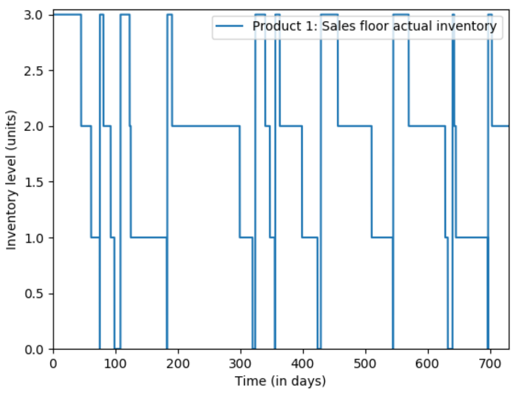

Figure 8-13: Sales floor inventory over time SKU 1

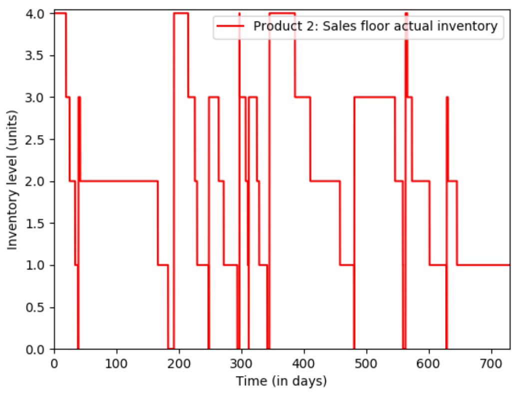

Figure 8-14: Sales floor inventory over time SKU 2

Verification 4 - Inventory losses and lost sales

The fourth verification is in terms of the structure different from the previous ones. In this verification, a hand calculation and a small check are used to verify the model.

Inventory losses
In the model there is a chance of 1.5% of inventory losses in the backroom as well as the sales floor. The first check is to test if the actual inventory losses match the chance on inventory losses. Hence, the number of lost items (N_{lost}) divided by the sum of lost items and number of sales (N_{sales}) should give the actual inventory losses (I_l) and it should match the expected value of losses l of around 3%:

$$I_l(\%) = \frac{N_{lost}}{N_{sales} + N_{lost}}. \tag{8-2}$$

Running the simulation model 25 times gives an average percentage of 3.06%. Hence, the actual inventory losses match the desired level.

Lost sales compared to percentage of OoSs
When a customer arrives in the store, there are two possibilities the item is available and the customer buys it, or the item is unavailable and the customer does not buys it (lost sale). Because substitutions are not taken into account, the average OoS percentage should be related to the lost sales divided by the sales and lost sales. The results for 25 simulation runs are presented in Table 8-3.

What can be seen is that the numbers are comparable, however, the lost sales are about 1% point lower than the calculated OoSs. This can be written off to the fact that the percentage of OoSs is always calculated at the end of each day before the replenishment. The lost sales occur throughout the day where the number of products on the sales floor is higher than at the end of each day.

Table 8-3: Verification 4 - lost sales compared to the percentage of OoSs

	Avg. OoS over total time	$\frac{N_{lostsales}}{N_{lostsales}+N_{sales}}$
Original situation	14.87%	13.78%
Deployment 1	7.39%	6.46%

8-3-2 Sensitivity analysis

Prior to the experiments, a sensitivity analysis is done into the influence of several variables on the percentage of OoSs. A sensitivity analysis is performed for the following variables: inventory losses, inventory turnover, lead time, replenishment thresholds and distributions. The sensitivity analysis are all performed for the traditional apparel store without RFID and RFID-deployment 1. Each configuration is simulated 100 times.

Inventory losses

In scientific literature studies, various variables are used for the inventory losses which can range between 0% and 7%. However, most of the studies research values up to 5%, because values above 5% are unrealistic. To determine the sensitivity for various numbers ranging between 0% up to 2.5% for the backroom and sales floor are analysed, resulting in total inventory losses of 0 % to 5% are analysed.

The sensitivity analysis gives the following results:

Table 8-4: Sensitivity analysis - inventory losses

	Inventory losses					
	0%	0.5%	1%	1.5%	2%	2.5%
Original situation	7.61%	10.13%	12.81%	15.25%	17.54%	19.65%
Deployment 1	7.58%	7.68%	7.73%	7.84%	7.93%	7.99%

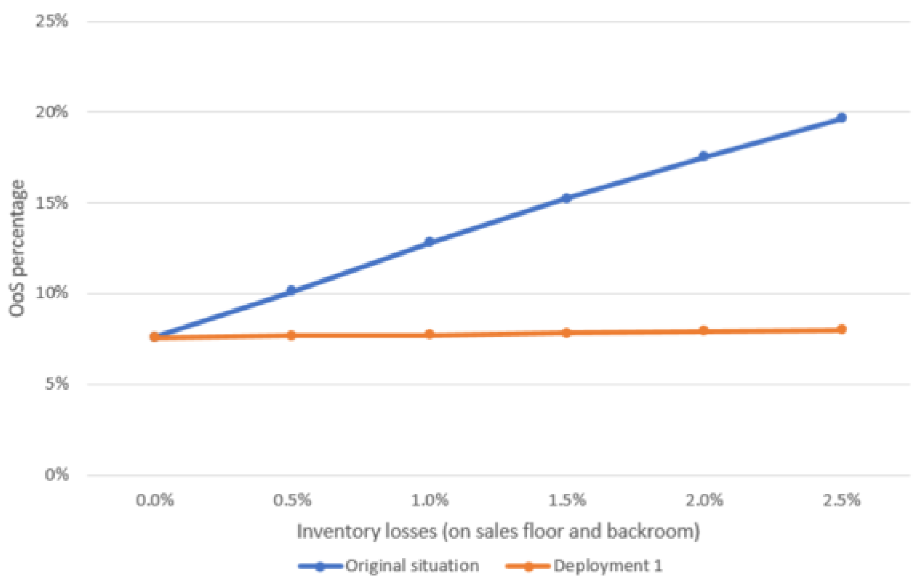

Figure 8-15: Dependence of OoSs on the percentage of inventory losses (percentages for backroom and sales floor)

From Figure 8-15, it can be concluded that there is a close to linear relationship between increasing the inventory loss rate and percentage of OoSs for the original situation. This is in line with the model, where inventory losses are the main cause for permanent OoSs. The line starts at a value of 7.6%, which is the natural temporary OoS percentage. This percentage, as well as the slope of the linear line are dependent on the store type. What is interesting is that the percentage of OoSs hardly increases with higher inventory losses for RFID-deployment 1. This is caused by the ability of RFID to frequently update the inventory record. From this sensitivity analysis can be concluded that RFID-deployments are more beneficial for stores with higher inventory losses. However, only compared to the original situation.

Inventory turnover

The average inventory turnover in the apparel retail industry is low compared to other retail industries. Scientific papers use significantly higher inventory turnover rates for their products compared to industry averages. Hence, the influence of the inventory turnover rate is also studied.

The sensitivity analysis gives the following results:

Table 8-5: Sensitivity analysis - inventory turnover

	Inventory turnover rate			
	3	5	8	12
Original situation	8.77%	15.24%	24.04%	34.68%
Deployment 1	4.85%	7.82%	11.95%	17.12%

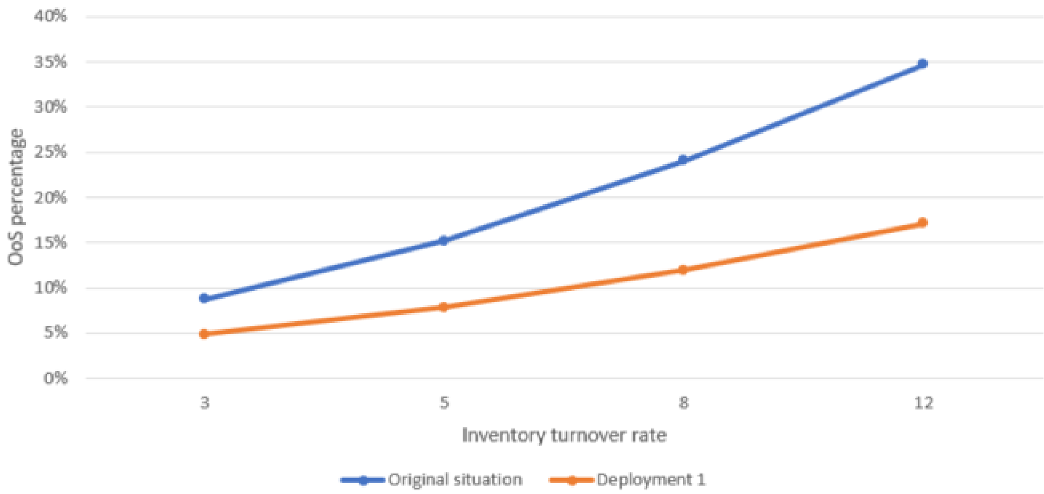

Figure 8-16: Dependence of OoSs on the inventory turnover rate

From Figure 8-16, it can be concluded that the inventory turnover does significantly influence the OoSs. In the original situation, the OoS percentage of an inventory turnover of 12 is almost 4 times as high as the OoS percentage by an inventory turnover of 3. In the situation of deployment 1, this is a factor of 3.5. Hence, it can be concluded that RFID has a better relative improvement for higher inventory turnover rates. Although the absolute percentage of OoS significantly increases. It must be noted that although the percentage of OoSs looks to increase exponential, the x-axis is not linear. This conclusion can therefore not be made from this figure.

Lead time

The time it takes to replenish a store is determined by the lead time. As discussed, this value is assumed to be 2 days. However, the longer the lead time, the higher the OoS can become. Furthermore, the replenishment in store only happens at the end of each day. This can influence the OoS percentage because the items can stay into the backroom until the next in-store replenishment. The influence of different lead times is therefore analysed.

The sensitivity analysis gives the following results:

Table 8-6: Sensitivity analysis - lead time

	Lead time (in days)				
	1	1.5	2	2.5	3
Original situation	14.34%	14.95%	15.18%	15.60%	15.80%
Deployment 1	7.03%	7.41%	7.84%	8.25%	8.67%

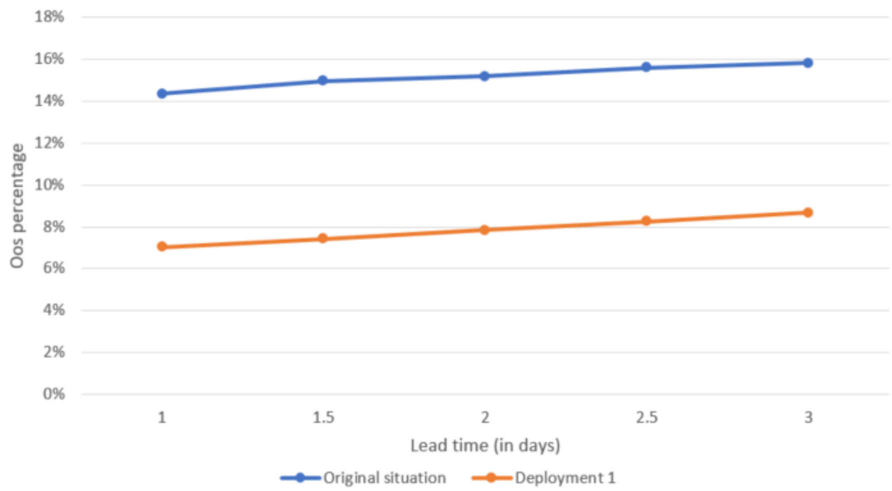

Figure 8-17: Dependence of OoSs on the lead time

From Figure 8-17, it can be concluded that increasing the lead time has an almost linear effect on the percentage of OoSs. However, the effect is fairly low compared to the inventory losses and inventory turnover.

Replenishment threshold

With a higher threshold value, items are ordered earlier. Although higher values are not in line with the calculation of the replenishment values, it could significantly reduce the number of OoS. The influence of adjusting the threshold value is therefore analysed.

The sensitivity analysis gives the following results:

Table 8-7: Sensitivity analysis - threshold value

	Threshold value			
	5%	10%	20%	40%
Original situation	15.29%	15.01%	11.72%	4.87%
Deployment 1	7.85%	7.83%	5.29%	1.99%

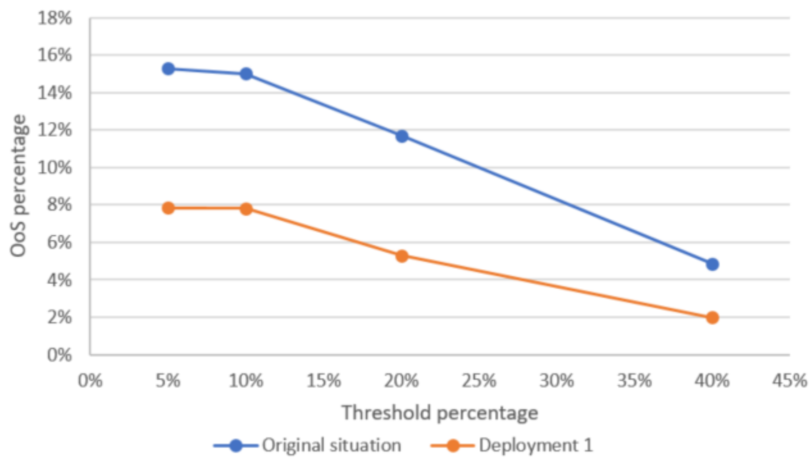

Figure 8-18: Dependence of OoSs on the threshold value

It can be concluded that a higher threshold value significantly reduces the number of OoS. This effect is slightly higher for RFID-deployment 1. This is a logical consequence of a higher inventory. However, a higher inventory comes with an increase in holding costs. It is therefore unrealistic to increase the threshold value.

Distributions

In order to verify the influence of several distributions, each distribution is made constant. The following distributions are tested: the inter-arrival time, the customer demand and the products per SKU. The results are shown in Table 8-8, where each distribution is made constant individually and simultaneously.

The sensitivity analysis gives the following results:

Table 8-8: Sensitivity analysis - distributions

Situation	OoS (%)
Original situation	15.21%
Customer arrival constant	15.19%
Customer demand constant	15.06%
Product quantities constant	13.67%
All above constant	13.46%

It can be concluded that changing the customer inter-arrival time or customer demand do not significantly influence the percentage of OoSs. However, changing the product quantities to a constant value does. This effect is caused by the fact that the demand is equal for each product irrespective to their quantity. The result is that in a range of product quantities, lower quantities have a higher inventory turnover, which results in a higher percentage of OoSs. In real retail stores, there are also products with a higher than inventory turnover rate. Although this effect can be partly compensated with forecasting, there are still a lot of uncertainties and forecasting is not included in is research. It is more realistic to have different quantities.

Conclusion

According to verification tests the model is successfully implemented. The graphical visualisations form a tool to identify the process behaviour and verify the output. The sensitivity analysis analyses the influence of different variables. This results in a insight into the dependence on several variables. All the results are a logical consequences of the model inputs, the model is therefore correctly implemented.

8-3-3 Validation

Model validation is usually defined to mean "substantiation that a computerised model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model" [Sargent, 2005]. In other words, validation is answering the question: Is it the right model? A validation is normally achieved by comparing the results to historical data or with what is expected based on historical data. In this situation, the model should be compared with data from a pilot store. Since the model is based on a constructed base model, it is impossible to validate the model by comparing the results with real data from the store. It can therefore not be determined if the model is absolutely valid. To absolutely validate the model, a pilot store must be set up in order to compare results or historical data of a store with multiple RFID-deployments should be used.

Regarding the goal of this research, comparing different RFID-deployments for various store types, a significant number of apparel stores would be necessary. Simultaneously, control stores are necessary to compare the results of RFID-deployments with, this would be impossible in the time span and possibilities for this research. This research is performed with the use of a simulation model based on a constructed research framework. In this model, parameters can be adjusted to mimic different store types with a single model in a limited time span. This should give a better understanding into the benefits of different RFID-deployments compared to scientific papers which study 1 product for 1 inventory system. The simulation model forms a fast and cheap way of comparing the impact compared to setting up many pilot store projects. Although pilot stores can give better results and even if many pilot store projects where performed, the same question arises as in this research. How representable are the results for other stores?

This question is hard to answer without analysing unique situations, comparing and adjusting the data and processes. To find the impact of the RFID-deployments for a specific apparel store, actual data from that store is necessary and the base model should be adjusted to that specific store. The store also must be further analysed if it matches the store processes assumed in this research. As discussed in the preliminary analysis, the model is not suitable for every type of apparel retail store. Since its assumes a constant inventory selection, which is replenished frequently. Hence, these assumptions must be considered in interpreting the results.

Conclusion

Following the validation, the simulation model only provides insight into the impact of RFID-deployments for various store types to a specific extent. This extent is limited because of the base model that is set up and the assumptions made to mimic various store types, which can not be absolutely validated. Hence, the model is the right model for filling in the research gap and answering this research question. However, it is not suitable to determine the precise percentage of OoS for every apparel retail store. If results for a specific apparel store are necessary, the input data and processes should be adjusted to match the characteristics of that particular store and the model should be verified and validated again.

8-4 Experiments

To answer the research questions, experiments are performed. Three main experiments are performed, in which a specific parameter is adjusted to change the store configuration. For each parameter adjustment, 100 simulation runs are performed for each RFID-deployment. The following 3 parameters are adjusted:

1. Ratios of the sales floor/backroom
2. Average number of products per SKU
3. Replenishment frequencies

The simulation period is 2 years and the results are only measured over the steady state period. The results are presented in tables.

8-4-1 Experiment 1 - ratio sales floor/backroom

The ratio between the sales floor and backroom determines how the products are divided between the sales floor and backroom. For example in the situation where the ratio is set on 0.25/0.75, then 25% of the products are moved to the sales floor and the rest is stored in the backroom. The following ratios are taken into account: 0.25/0.75, 0.5/0.5, 0.75/0.25.

Experiment 1 gives the following results:

Table 8-9: Results experiment 1 - OoS percentages for the different sales floor/backroom ratios

	Sales floor/backroom ratio		
	0.25/0.75	0.5/0.5	0.75/0.25
Original situation	17.51%	15.15%	14.90%
Deployment 1	9.30%	7.84%	8.25%
Deployment 2	9.10%	7.65%	7.50%
Deployment 3	9.08%	7.67%	7.44%
Deployment 4	9.05%	7.68%	7.47%

8-4-2 Experiment 2 - quantities per SKU

Each SKU has a different quantity. These are randomly picked from a uniform distribution. The standard average is 6, ranging the distribution from 3 to 10. It is determined to study a lower and a higher average quantity, including a descresing or increasing range. The following tests are performed:
- Quantities between 1,6 with an average of 3.
- Quantities between 3,10 with an average of 6.
- Quantities between 8,17 with an average of 12.

Experiment 2 gives the following results:

Table 8-10: Results experiment 2 - OoS percentages for the different quantities per SKU

	Average quantity per SKU		
	3	6	12
Original situation	12.28%	15.15%	16.04%
Deployment 1	8.62%	7.86%	4.88%
Deployment 2	8.42%	7.71%	4.75%
Deployment 3	8.43%	7.67%	4.69%
Deployment 4	8.39%	7.65%	4.62%

8-4-3 Experiment 3 - replenishment frequency

In experiment 3 are the replenishment frequencies adjusted. The base store is replenished once a week and the sales floor is replenished once a day. The to-store replenishment is varied from once every 3 days up to 14 days and the in-store replenishment is varied between once an hour and once a day.

Experiment 3 gives the following results:

Table 8-11: Results experiment 3 - OoS percentages for the different replenishment frequencies

	To-store: 3 days In-store: 1 hour	To-store: 3 days In-store: 1 day	To-store: 7 days In-store: 1 hour	To-store: 7 days In-store: 1 day	To-store: 14 days In-store: 1 hour	To-store: 14 days In-store: 1 day
Original situation	11.54%	13.31%	13.69%	15.14%	16.96%	18.28%
Deployment 1	3.95%	5.72%	6.10%	7.86%	9.57%	11.29%
Deployment 2	3.86%	5.63%	6.00%	7.70%	9.46%	11.12%
Deployment 3	3.85%	5.62%	5.95%	7.65%	9.43%	10.08%
Deployment 4	3.81%	5.58%	5.92%	7.65%	9.37%	11.03%

8-5 Analysis of the results

Different elements can be noticed from the experimental results. First of all, for every store configuration in each experiment, RFID significantly reduces the percentage of OoSs. The differences between the RFID-deployments are relative to each other quite small even in the most frequent replenished situation.

The results of experiment 1 show that a smaller sales floor results in a higher OoSs percentage. This effect can be seen in the original situation as well as the RFID-deployments. It must be noted that the differences between 0.5/0.5 and 0.75/0.25 are a lot smaller than between 0.25/0.75 and 0.5/0.5.

The results of experiment 2 show that a higher number of items per SKU results in a higher percentage of OoSs in the original situation. However, the opposite effect is seen with the RFID-deployments, where a higher number of items per SKU results in a lower percentage of OoSs. It is therefore interesting to analyse is the improvement of the RFID-deployments compared to the original situation.

The results of experiment 3 show that more frequent replenishment results in less OoSs in the original situation as well as with RFID-deployments. However, a higher RFID-deployment is not better for a more frequent replenishment than a less frequent replenishment relative to the first RFID-deployment.

8-5-1 Improvement compared to the original situation

To check the improvements for a specific store configuration, the RFID-deployments have to be compared with the original situation for a specific configuration. Hence, the relative improvement is measured. The relative improvements are presented in Tables 8-12, 8-13 and 8-14.

Table 8-12: Experiment 1 - relative improvement: ratio sales floor/backroom

	Sales floor/backroom ratio		
	0.25/0.75	0.50/0.50	0.75/0.25
Deployment 1	46.89%	48.27%	48.82%
Deployment 2	48.01%	49.51%	49.63%
Deployment 3	48.12%	49.40%	50.04%
Deployment 4	48.30%	49.31%	49.86%

Table 8-13: Experiment 2 - relative improvement: quantities per SKU

	Quantity per SKU		
	3	6	12
Deployment 1	29.75%	48.14%	69.58%
Deployment 2	31.40%	49.10%	70.39%
Deployment 3	31.32%	49.36%	70.73%
Deployment 4	31.61%	49.53%	71.21%

Table 8-14: Experiment 3 - relative improvement: replenishment frequencies

	To-store: 3 days In-store: 1 hour	To-store: 3 days In-store: 1 day	To-store: 7 days In-store: 1 hour	To-store: 7 days In-store: 1 day	To-store: 14 days In-store: 1 hour	To-store: 14 days In-store: 1 day
Deployment 1	65.79%	57.06%	55.41%	48.05%	43.55%	38.24%
Deployment 2	66.58%	57.73%	56.18%	49.11%	44.22%	39.17%
Deployment 3	66.66%	57.79%	56.52%	49.46%	44.42%	39.40%
Deployment 4	66.97%	58.10%	56.79%	49.47%	44.74%	39.69%

It can be seen that there are some major differences in the results. For example, stores with higher quantities per SKUs and those that are often replenished show relatively high improvements compared to stores with lower quantities and the stores that are replenished less frequent. The differences between the improvements for different sales floor/backroom ratios are minuscule.

8-5-2 Improvement compared to the increase in inventory

The results for the RFID-deployments show significant improvements in the reduction of OoS. Another way to reduce the number of OoS is doubling the inventory. However, in apparel stores it is key to find a balance between minimal OoSs and minimal overstocks, because extra inventory comes at extra costs. Since, RFID can increase the average inventory, it should therefore be taken into account.

In order to determine the exact balance between the benefits of reducing the number of OoS and the costs of extra inventory, a comprehensive economical analysis is necessary which is unique for every apparel store. An economical analysis is not part of the research scope. However, there is another way to determine if the RFID-deployments are viable.

The method is explained with an example. The percentage of OoS in the original situation is 15%, resulting in an availability of 85%. As a result, for every 100 customers about 85 items are sold. As the OoS percentage decreases to 5% as a result of RFID, 95% is available resulting in 95 sales. The result is an increase in sales of 11.7%. A similar calculation can be performed for the average inventory. Comparing these improvements can be used to determine if the benefits of increased sales out weight the extra inventory.

The example is more clearly explained in Table 8-15, where the factor is calculated by dividing the sales increase with the inventory increase.

Table 8-15: Examples of the relative improvement factor

	Situation A		Situation B		Situation C		Situation D	
	Sales	Avg. Inv.	Sales	Avg. Inv.	Sales	Avg. Inv.	Sales	Avg. Inv.
Original	85.0%	500	85.0%	500	85.0%	500	85.0%	500
RFID	95.0%	550	95.0%	500	95.0%	559	95.0%	1000
Increase	11.8%	10.0%	11.8%	0.0%	11.8%	11.8%	11.8%	100.0%
Factor	$1.18 \geq 1$, OK		$\infty \geq 1$, OK		$1 \geq 1$, OK		$1 \geq 0.118 \geq 0$, Unknown	

If the factor equal to or is higher than 1, the improvement is always beneficial, assuming that the current store in beneficial. If the factor is between 0 and 1 it is not possible to determine if the improvement is beneficial without an extra economical analysis. If the percentage of OoSs increases, the deployment is not beneficial.

For each deployment, the relative improvement factor is calculated and presented in Tables B-1, B-2 and B-3. The corresponding average inventory for each deployment and store configuration is in Appendix B-4.

Table 8-16: Experiment 1 - relative improvement factor: sales floor/backroom ratio

	Sales floor/backroom ratio		
	0.25/0.75	0.50/0.50	0.75/0.25
Deployment 1	2.28	1.66	1.44
Deployment 2	2.31	1.69	1.43
Deployment 3	2.39	1.60	1.37
Deployment 4	2.33	1.89	1.44

Table 8-17: Experiment 2 - relative improvement factor: average quantity per SKU

	Quantity per SKU		
	3	6	12
Deployment 1	1.80	1.72	4.37
Deployment 2	1.60	1.74	4.71
Deployment 3	1.49	1.65	4.35
Deployment 4	1.43	1.71	3.86

Table 8-18: Experiment 3 - relative improvement factor: replenishment frequency

	To-store: 3 days In-store: 1 hour	To-store: 3 days In-store: 1 day	To-store: 7 days In-store: 1 hour	To-store: 7 days In-store: 1 day	To-store: 14 days In-store: 1 hour	To-store: 14 days In-store: 1 day
Deployment 1	1.75	1.64	1.63	1.76	1.93	1.80
Deployment 2	1.75	1.66	1.62	1.75	1.80	1.72
Deployment 3	1.77	1.65	1.55	1.68	1.89	1.84
Deployment 4	1.70	1.67	1.53	1.64	1.75	1.68

All the store configurations show values higher than 1. Hence, all deployments are viable. It must be noted that for a real economical analysis, more information is necessary. These factors only show that the increase in sales is higher than the increase in average inventory, and that if only these factors would count, the deployments are beneficial.

Conclusion

This chapter presented the experimental plan, which started with presenting the hypotheses, where after is determined that an initialisation period of 1 year, the total simulation time of 2 years and 100 runs per configuration should be used. The simulation model is calibrated by adjusting the lead time, inventory turnover, adding errors to the delivered goods and rounding the threshold values to match the results found in the literature more closely. The model is verified with the use of a few tests and a sensitivity analysis. It is determined that the model is not absolutely valid because of the lack of real data to compare the results with.

The experiments show that RFID significantly reduces the number of OoSs for each store configuration. Ranging from about 30% to about 70%, with an average of 49%. Relative to each other, the RFID-deployments barely differ regarding the reduction in OoSs. Store configurations do have an impact on the percentage of OoSs, especially in combination with

RFID-deployments. The effect is limited for the different sales floor/backroom rations. However, is large in the experiments regarding the average quantity per SKU and different replenishment frequencies. Other store characteristics as: the threshold percentage and inventory turnover also significantly influence the percentage of OoSs for the original as well as the RFID-deployment. Inventory losses only influences the percentage of OoS in the original situation. The lead time only has a small impact on the OoSs.

Chapter 9

Conclusion and discussion

The first part of this chapter presents the conclusion of the research, including answers to the main- and sub-questions. The second part presents the discussion of the research, recommendations for follow up research and a view of the possible future of apparel retail.

9-1 Conclusion

Recent years have been disruptive for many retail stores. High competition, offline as well as online, and increasing customer demands are the main reasons. One of the key requirements for retailers to be competitive is to have at least a high variety of products, which are always available. Since, Out of Stocks (OoSs) directly result in lost sales and indirectly result in a decline in reputation.

Automated replenishment systems are often used to aid on item availability. The problem is that these systems are based on inaccurate inventory records. Simultaneously, there is a lack of information to compensate the discrepancy between the actual and recorded inventory. Radio Frequency IDentification (RFID) enables retailers perform inventory counts more frequently. More information about their inventory leads to improved inventory records. This results in an improved replenishment and reduces the number of OoSs. However, different RFID-deployments exist, which can have different effects on various store types.

The goal of this research was to compare different RFID-deployments for various store configurations regarding the reduction of OoSs. To analyse the impact of the different RFID-deployments, the main research question is answered.

To what extent does more information, obtained by different RFID-deployments, result in less out-of-stocks for various apparel store configurations?

Following the results of the experiments, more information in terms of a more frequent inventory count reduces the percentage of OoSs significantly for each store configuration. However, only to a specific extent. A more frequent inventory count by a higher RFID-deployment does not reduce the number of OoSs significantly more than RFID-deployment 1. The results for RFID-deployments compared to the original situation range significantly. A reduction of 29.7% is achieved with an average product quantity of 3 items per Stock Keeping Unit (SKU). A reduction up to 71.2% is achieved with an average product quantity of 12 items per SKU. The lowest achieved number of OoSs can be found for deployment 4, where the store is replenished every 3 days and the in-store replenishment performed hourly, which is 3.8%. For the base store, RFID reduces the percentage of OoSs from about 15% to 7.7%. It can be concluded that more information obtained by RFID, significantly reduces the number of OoS. However, an inventory scan more frequent than once a week has almost no effects. For a further decrease of the number of OoSs, other store characteristics or processes in the retail store have to be changed.

To answer the main research questions, the following sub-questions were answered:

How is the apparel retail sector transformed up to today and why is this research relevant nowadays?
The retail industry is transformed from a retailer centric point of view, where the retailer had limited competition and could determine what the customers were able to buy, to a customer-centric point of view. The primary cause is competition. Offline competition from new store concepts, which specialise or offer discount products. As well as online competition, which have major assortments in which products are always available. The result is that customers are more demanding than ever before. Hence, retailers have to have at least a high variety of products that are always available. RFID enables the possibility to obtain more information about their inventory to improve the replenishment process. Since the technology has matured and became affordable over the last 10 years, it is rapidly gaining popularity in recent years. More and more retailers are looking into the possibilities to implement RFID-deployments in their retail stores.

What elements of RFID based replenishment in retail stores are discussed in the literature?
The literature presents several studies regarding RFID based store replenishment. It often only studies handheld readers as RFID-deployment with one type of a Fast Moving Consumer Good (FMCG) in combination with case-level tagging, instead of item-level apparel tagging. Simulation studies of retail stores usually have an unlimited backroom or are simulated as one inventory system. The only studies that use item-level tagging for apparel stores are studies regarding pilot projects, but those studies are limited to one particular store. What is missing is a study that compares different RFID-deployments for various apparel store configurations.

What is the current problem in retail stores, what is more information and how can it be used to solve the problems?
The problem in this research are OoSs in apparel stores, resulting in lost sales in the short term and a declining brand reputation in the long run. The two leading causes of OoSs are inventory losses, mainly caused by internal and external theft, and a lack of information to compensate these irregularities. As a result, a growing discrepancy between the actual and recorded inventory arises over time. Since automated replenishment systems are based on the recorded inventory, the discrepancy leads to a growing number of OoSs. With the use of RFID, more frequent inventory counts can be performed resulting in an improved inventory accuracy. Replenishment based on more accurate inventory records results in less OoSs.

What are the different RFID-deployments and to what extent can they obtain more information?

Four RFID-deployments are compared in this research, namely: 1) handheld readers, 2) a robot readers, 3) a combination of overhead and handheld readers and 4) only overhead readers. These RFID-deployments are distinguished by their frequency of scanning the complete inventory. Ranging from once a week for handheld readers up to a continuous inventory scan by overhead readers. The deployments are compared to a traditional retail store without RFID that counts its inventory only twice a year.

What are the different types of apparel store configurations?
Each retail store is unique, without data it is unable to model a specific store accurately. To keep the research generic and analyse the effects of specific parameters a base model is constructed and only one parameter is adjusted each time. The parameters that are adjusted are the ratio between the sales floor and backroom, the average number of items per SKU and the replenishment frequency. These parameters can be compared with characteristics of a specific store type. For example, a shoe store has a small sales floor/backroom ratio compared to a department store. An exclusive store has lower quantities per SKU than a discount store. A major store close to a Distribution Centre (DC) is replenished more frequent than a smaller remote store.

How can the different RFID-deployments be compared for different store configurations?
The performance of different deployments and store configurations are compared with the use of a discrete event simulation. A simulation can be used as a decision tool and is a fast and cheap way to compare the influence of different parameters on a system. The disadvantage is that the results are less representable than results from an actual pilot store. For each RFID-deployment and store configuration, the average OoS percentage is measured. These are compared to the original situation and to the change in average inventory to determine if the RFID-deployment is viable.

To what extent do the RFID-deployments reduce the number of OoSs for the different experiments?
According to the results of the experiments, RFID reduces the number of OoSs in the range between 29.7% and 71.2%, with an average of about 49%. The reduction is more or less similar for the different ratios between the sales floor and the backroom. However, the results vary significantly when different quantities per SKU are used. An average quantity of 12 items per SKU, results in an average reduction in OoSs of 70%. RFID for an average quantity of 3 results in a reduction in OoSs of 31%. Similar differences are seen with varying the replenishment frequency. A to-store replenishment once every 3 days and an in-store replenishment hourly results a reduction in OoSs of 66%. A to-store replenishment of once every two weeks and an in-store replenishment once a day results in a reduction of 39%. The results between different RFID-deployments, for constant store configurations, hardly differ from each other.

It can be concluded that RFID reduces the OoSs significantly for each store configuration, if it is used to count the inventory more frequent. The results are similar for each RFID-deployment; a higher RFID-deployment does not lead to a substantially lower percentage of OoSs. Purely on the basis of the results of this research, it is not necessary to install a higher, more expensive, RFID-deployment to reduce the number of OoS further. However, a higher deployment could have other benefits if other performance indicators are used. For example the dependency on employees or a recent confirmation of the location of an item to reduce the number of OoSs. To be prepared for the future in the changing retail sector, retailers should invest in RFID. Not only to directly reduce their OoSs but also to enable other benefits and not fall behind their competition.

Omni-channel retailing is often named in discussions about RFID in the apparel retail sector and the future of apparel stores. However, in practise retailers have other priorities regarding the implementation of RFID-deployments and handheld readers are therefore sufficient. Eventually, most retailers will transform their retail concepts more to omni-channel retailing. To completely transform to omni-channel retailing, RFID-deployment 4 is necessary.

9-2 Discussion

Many future ideal situations are directly outlined when a new technology arises. In reality, however, apart from a few pilot projects, the technologies and possibilities are often only partly implemented. This is a result of the fact that new technologies are often unknown, only partially developed, too expensive, the benefits are unclear or because of resistance to change. Studies can help to fill in knowledge gaps or elucidate the benefits or drawbacks of technologies. This study tries to create more understanding into the benefits of RFID for several types of apparel store configurations. However, as in all studies, the research has several limitations. This chapter gives a reflection on the research, presents suggestions for follow up research and gives a view of the possible future of apparel retailing.

9-2-1 Discussion of the research

The simulation model is built to get an understanding of the benefits of different RFID-deployments. To keep the model generic and be able to compare several configurations for different RFID-deployments, simplifications and assumptions had to be made and certain elements are left out. This results in several limitations, which are discussed in this section.

Regarding the base model, several assumptions were made to create the base model. For example, weekly replenishment to-store, daily replenishment in-store, an inventory turnover of 5, sales floor/backroom ratio of 0.5/0.5. These assumptions are based on values found in the literature. However, it must be noted that there is no such thing as a standard or average retail store. Every retail store is unique and has its unique characteristics. In order to compare the RFID-deployments, a generic base model based on assumptions had to be created. The model does not present a real retail store, but it enables the possibility to compare the influence of different parameters.

The representation of the inventory in the base model is limited compared to a real inventory. It is assumed that the store has a standardised collection, which is always replenished. In reality, stores often have a seasonal collection besides their standard collection. These are not or only replenished for a limited period. In such situations, stores could be more careful with ordering high quantities at the end of the season, or it is unable to replenish the items since they are already completely sold out. The question that arises here: are items OoS if a policy until supply lasts is used and the items are then removed from the assortment. Furthermore, in reality, items differ in demand. For example, common sizes are sold more frequent than extreme sizes. This is a factor manufacturers or retailers can take into account. What models become popular and are sold frequently is harder to estimate. In order to compare different store configurations, the inventory was simplified to uniform products with a random demand, which are always replenished.

Several less significant elements are left out of the model. For example, customers can ask employees if an item is still available in the backroom, customers can return items which are damaged or items could be transferred to another store. These elements are small compared to the processes simulated. However, they exist and could influence the results. Since, these factors can not be measured with the model, leaving them out limits the model.

Furthermore, the research and model is limited to one problem in the retail stores, namely OoSs. Other problems should also be taken into account to get a more complete overview of the potentials of RFID.

Regarding RFID, the research limits the differences between the deployments to the frequency of the inventory count. In reality, more factors should be taken into account. For example, lower read rates due to physical constraints or misuse by employees. Or a reduction in shrinkage due to the RFID-deployments. This can be achieved with overhead readers that can detect movements. For example, movements of items that have not yet been paid for in the direction of the exit. Another benefit is that customers and employees are less tempted to steal if they know that every item is being watched. These benefits and drawbacks are also unique for every retail store. Due to the nature of the technology, physical constraints and customer demands, all deployments apart from the handheld-readers are custom made. Handheld-readers are on their turn dependent on how employees use them.

Furthermore, even if a real store was used and many of these factors were known, there are several elements which are extremely hard to simulate. People, both employees and customers have unique characteristics, preferences, make mistakes, do unexpected things and differ per location. They are therefore challenging to model correctly. The same accounts for external factors as: changing fashion trends, long-term customer experiences, the increase or decrease in the arrival rate of customers, the weather and local competition. All these factors can influence the number of OoSs.

The conclusions of the research are also limited by the fact that a complete cost-benefit analysis is not made. As discussed, many factors are unknown and should be looked into separately. For example, the costs of different deployments, software as well as hardware, labour cost reduction, and factors as long-term customer experiences. As a result of these limitations and the lack of a validation with the use of a real store, only general conclusions are possible. Detailed precise reductions in the percentage of OoSs are unique for every situation and can not be derived from this model alone.

9-2-2 Follow up research

To overcome the limitations or to extent this research, following suggestions are made: a) extent this research by improving or removing the limitations, b) research into the other elements of the cost-benefit analysis to get a complete overview, c) use a pilot store to test the deployments for a real store.

Model
Several elements are simplified or left out in the simulation model. Follow up research is

recommended into the following fields to overcome the limitations of this study. Focus on one type of store and adjust the base model accordingly, this should give more representable results. The variations when looking at one type of apparel store should be less significant than comparing apparel stores in general. The improvements can be mainly achieved with the use of actual data. Generate an improved inventory, use actual replenishment data and add small item flows as returns. Furthermore, the differences between the RFID-deployments could be modelled more realistic. For example, including a location where the item is last seen, adjusting the accuracy of inventory scans to the different deployments. Hence, if scanned more frequently, for example, multiple scans overnight, the total inventory accuracy increases compared to a single handheld inventory scan.

Cost-benefit analysis
The second recommendation for follow up research is to extent the cost-benefit analysis. For example: add labour cost reduction regarding the search for items, receiving items, the improved processing of returns, and the inventory counts. The economical benefits of increased sales and including the costs of each implementation. A complete cost-benefit analysis should give a more comprehensive overview of the benefits and drawbacks of each deployment. However, if specific economic variables are used the scope will be limited to one type of store.

Pilot store
The third recommendation is to use a pilot store to obtain data for the model, to validate the data or to verify a potential solution with actual tests. This will increase the credibility of the research. However, it must be noted that completely different limitations will arise when setting up a pilot. For example, incorrect master data, wrong RFID-tags, manually adjusted tags, items that should be in-store are not seen (unknown if stolen, returned, transferred), loss of tags and errors in manually scanning. Furthermore, the scope will be limited to one type of store.

9-2-3 Future of retailing

The rate in which technological developments with a significant influence on our daily life are being implemented is continuously increasing. There are always sceptics at the beginning of a new technology. However, over time the benefits will become clear, the technology becomes cheaper and is used more frequently, until it is widespread. Persons or companies who do not adjust are left behind. A similar phenomenon was seen in the retail sector before. When the first barcode scanners were used, some found them to be too expensive or unnecessary. When the first online retailers started to arise, offline retailers thought that customers would not purchase their clothes online. Nowadays every store has a barcode scanner, and most of the retailers are also present online.

Near future

It is likely that the use of RFID in apparel retail stores follows the same path. Several benefits such as a higher inventory accuracy, the corresponding reduction of OoSs or the possibility to locate items will become a standard. Furthermore, data is becoming increasingly important in all types of logistical processes. In apparel stores, more accurate data can, for example, be used to predict demand more accurately. RFID is essential to obtain the necessary data.

The next step for retailers to set them apart from their competition is probably omni-channel integration, where the retailer offers a full integration between online and offline channels. The offline stores will be supported by RFID, where overhead readers present most benefits. For example: locating items precisely, automated checkouts, social shopping, interaction with the customer based on his location, preferences and what items he or she has picked up and cross-selling. For example with the use of magic mirrors. Since these improvements are not all-or-nothing challenges, elements can probably be seen more and more in the following years. However, these developments are perhaps not seen in all retail store concepts in the near future. For example, a cheap discount store with the policy while supply lasts is not likely to introduce RFID in the following years.

Future store

The above example assumed that apparel retail stores would continue to exist in more or less their traditional form. However, there are chances that the apparel retail sector will completely change due to technological development. For example, the combination of a 3D body scanner, augmented reality, sewing robots, a lot of information on the customers' preferences and Artificial Intelligence (AI). This could result in a store, where a customer could walk in and make a 3D body scan to measure his or her body. AI simultaneously analyses the customers' preferences based on all the offline and online purchases in the last ten years, likes on social media and other data of the customer that is available. It combines these with local and worldwide fashion trends and completely designs a vast selection of custom made clothes. The customer can directly virtually fit the items with augmented reality. Several fabrics are available in-store, to see the colours in real life and feel their quality. The customer selects the desired designs and purchases them. The orders are directly sent to a high tech factory, where robots make the items overnight and deliver them the next day to your home. Although this example is a made up fictional store and sounds like a science fiction movie, it could happen in the next years. Because 3D body scanners, augmented reality to fit clothes, AI that presents suggestions based on previous bought items and general trends, an AI fashion designer, sewing robots and one-day delivery all already exist individually ([Sun, 2017], [Hobson, 2015], [Knight, 2017], [Bain, 2017]).

Appendix A

The Appendix

A-1 Scientific paper

The scientific paper starts at the next page.

The impact of RFID-deployments on Out-of-Stocks in various apparel stores

D.S. de Boer[1], I. Van der Zanden MSc[2], Dr. Ir. Y. Pang[1], Prof. Dr. R.R. Negenborn[1]

***Abstract*—OoSs in apparel stores lead to lost sales in the short term and a decline in reputation in the long run. The main reason for an increasing number of OoSs is the discrepancy between the actual and recorded inventory. The discrepancy increases over time due to random inventory losses, mainly due to theft. One of the solutions is to increase the frequency of the inventory counts to align the recorded inventory with the actual inventory. Frequent inventory counts are only possible with the use of RFID-deployments. Each deployment is linked to a specific inventory count frequency and can have different effects on various retail stores. This research compares the deployments with the use of a discrete event simulation model. The results show that RFID significantly reduces the number of OoSs for each store type. According to the experiments, it is not necessary to implement a higher RFID-deployment if the only performance indicator is OoSs. Furthermore, the research analysis the sensitivity of several important variables and tests if each RFID-deployment is viable.**

***Keywords*—RFID, Out-of-Stocks, replenishment, retail.**

I. Introduction

Recent years have been disruptive for retail and chain stores [Consultancy.nl, 2016]. Retailers are struggling to keep up with the substantial changes in the retail landscape. The most disruptive changes are the rise of e-commerce and new retail concepts. Simultaneously, retailers see an increase in the diversity of customer groups [Gagnon and Chu, 2005]. These changes have resulted in customers that are not only more demanding and price-conscious than ever before, their behaviour has become increasingly difficult to predict [Thiesse and Buckel, 2015]. One of the results is that retailers should have at least a high mix of decently priced products which are always available in order to compete.

It is key for all retailers to ensure a high product availability and to minimise overstock or out-of-stock (OoS) events [Iannone et al., 2015]. This is extra important for apparel stores, where 'Web-rooming' is becoming more important. Web-rooming is the practice of researching items online and then purchasing them in-store [Säilä, 2016]. [Footfall, 2016] even suggests that 55% of the customers know exactly what they are looking for. On the other hand, for customer who do not know what they want, better displays with sufficient inventory, strongly drive sales [Mou et al., 2017].

Automated replenishment systems are often used to aid on item availability. The problem in retail stores is that the replenishment systems are often based on inaccurate inventory records. These inaccurate records can compromise item availability [Kang, 2004]. The problem is that it is not realistic to obtain a high inventory accuracy with traditional manual counting and bar-codes, due to the costs of human labour and their error sensitivity [Kök and Shang, 2007]. Radio Frequency IDentification (RFID) is one of the most promising techniques to obtain the necessary information [Nayak et al., 2015]. It is gaining more and more attention in recent years since the technology has matured and is becoming increasingly affordable. RFID enables the possibility to scan the inventory much faster, often resulting in a more frequent inventory count [Bertolini et al., 2012].

The objective of the research is to compare the influence of the different RFID-deployments for various store configurations regarding the reduction of OoSs. To achieve this objective, the following research question is answered:

To what extent does more information, obtained by different RFID-deployments, result in less out-of-stocks for various apparel store configurations?

The different RFID-deployments are compared with the use of a discrete event simulation made in Python. Variables are adjusted to mimic different situations and compare their influence on the reduction of OoSs. The remainder of the paper is organised as follows. The next chapter provides a review of prior research on RFID based replenishment in retail stores. Chapter III analyses the retail store as a system, including the replenishment and different RFID-deployments. Chapter IV discusses the simulation model. Chapter V presents the results of the experiments. The paper closes with the conclusion of the research and a discussion of the limitations and opportunities for follow-up research.

II. Literature review

A number of studies into RFID based replenishment in retail stores have been conducted. Several are highlighted. [Kang, 2004] shows with a simulation model, that small inventory losses can lead to severe OoSs. The extra revenue losses of these OoSs are higher than the initial inventory losses [Kang and Gershwin, 2005]. [Wong and McFarlane, 2007] describes that the final few meters of a supply chain are critical to the performance of the whole supply chain. It explains the key factors regarding shelf replenishment and recognises the potentials of RFID in theory. The study does not use quantified data or calculations to support their theories and focuses on grocers instead of apparel retailers. A simulation study of RFID enabled shelf replenishment for a FMCG is presented in [Thiesse et al., 2007]. The study uses case-level tagging for a

1. Department of Transportation Engineering Logistics, Delft University of Technology - Delft, Netherlands
2. Mieloo & Alexander Business Integrators - Hoofddorp, Netherlands

specific product and concluded that the maximum benefits can only be drawn from RFID if decisions on the optimisation of shelf space are being made in parralel. [Condea et al., 2012] is an extension to prior research, which takes detection errors into account. The study concludes that RFID has the potential to improve service levels. However, different cost factors and read rates must be considered. This research is focused on one product and case-level tagging. [Thiesse and Buckel, 2015] concludes that read rates significantly impact the costs, especially for case-level tagging. However, it considers data from two grocers and two apparel stores. The main interferences are caused by water and metallic objects. [Bertolini et al., 2012] is an experimental study that follows 20.000 garments in a Italian apparel store. The research shows that an inventory accuracy between 97% and 99.54% could be obtained. The paramount outcome of the research is that RFID can significantly increase the turnover. Optimising the replenished increased the turnover between 4.9% to 11.2% and employees knowing what is still available in the backroom to sell the items directly resulted in an increase of 0.8%. [Bottani et al., 2016] proves that RFID can improve the sales turnover in a fashion retail store, where RFID is used to provide an updated inventory replenishment list. This way the manager knows which items he can replenish. However, the research only followed 10 items that were frequently sold during the week days. It concludes that availability leads to a significant increase in the sales volume and that the availability of products on shelves stimulates customers to ask for different sizes and models, generating further potential for sales increase. [De Marco et al., 2014] models the effectiveness of RFID technologies in improving sales performance in fashion retail outlets. It acknowledges that there is a lack of information regarding item-level tagging in stores. Critical in this particular retail store is staff-assisted sales. The research concludes that a lot of staff time can be saved with the use of RFID.

It can be concluded from the literature that RFID has the potential to increase the sales turnover, mainly by reducing the OoSs. Sub-optimal read rates play a role for grocers with case-level tagging, not for item-level tagging in the apparel retail. RFID handheld readers enable fast inventory counts, other readers are hardly independent of humans and therefore can perform event faster counts are discussed in the literature. As is item-level tagging for apparel in general, except for a few pilot stores. The studies that used simulations were focused on one FMCG and assumed a retail store with an unlimited backroom or without a division between the backroom and sales floor.

Hence, there is a research gap between fundamental research that shows the potential benefits based on a simple simulation with one product and extensive pilot stores project. The problem with pilot store projects is that they are limited to a specific store and that often only one RFID-deployment is taken into account. The research gap is shown in Figure 1.

A cost-benefit analysis is normally made before a large project. The same accounts for retailers regarding RFID deployments. Filling up the research gap should give retailers a better understanding into the benefits of the analysis for different RFID deployments in various store types regarding the reduction of OoSs.

Fig. 1. The research gap

III. Analysis

The system studied is a mortar and brick store. The black box of a retail store is shown in Figure 2. The goal of the retail store is to sell as many items as possible. It is assumed that a constant amount of customers arrive each day. To increase the sales: items have to be available.

Fig. 2. Black box of a store

To aid on item availability, inventory systems are used. The inventory of a specific stock keeping unit (SKU), I_{k+1}, is calculated with equation 1. In which I_k is the previous inventory, a_k the arrived items and e_k the sold items

$$I_{k+1} = I_k + a_k - e_k. \tag{1}$$

The total inventory, I_t, can be calculated with equation 2.

$$I_t = \sum_{i=1}^{n} I_i^k. \tag{2}$$

A. Store control

Replenishment of inventories is based on two key elements: the replenishment logic and item visibility. The replenishment logic determines when and what quantities are ordered. In this research (R,s,S) replenishment logic is used. R is the review time, s is the threshold value and S is the order up to point. The replenishment logic can not be properly applied if the inventory is unknown. Inventory visibility is therefore of key importance and is often missing in retail stores.

The problem in retail stores is that inventory losses occur and that there is a lack of information to compensate the errors. As a result, over time a discrepancy arises between the recorded and actual inventory. Equation 3 is in reality, the recorded inventory, I_{k+1}. The actual inventory, I_{k+1}, is given with equation 4, in which inventory losses, l_k, are added.

$$\tilde{I_{k+1}} = \tilde{I_k} + a_k - e_k. \tag{3}$$

$$I_{k+1} = I_k + a_k - e_k - l_k. \tag{4}$$

B. Inventory accuracy

The problem is the discrepancy between the recorded, $\tilde{I_{k+1}}$, and actual, I_{k+1}, inventory. The discrepancy is called inventory record inaccuracy (IRI) [DeHoratius et al., 2008]. Numbers of the magnitude of IRI differ significantly in the literature, depending on the type of store, type of products and how and when it is measured. The study of [DeHoratius and Raman, 2008] finds the IRI to be around 65% after examining nearly 370.000 inventory records. Other studies find IRIs of 51% [Kang and Gershwin, 2005] and 55% [Gruen and Corsten, 2007]. Or measure the IRA and find values of 60% [Doyle, 2016], 65% [Joseph and Kaur, 2017] or 67.4% [Salmon, 2016]. In this research, the inventory record accuracy (IRA), represented with R_a, is measured with equation 5, in which n is the number of SKUs, Q_i^a is the actual quantity and Q_i^r the recorded quantity.

$$R_a(\%) = \frac{\sum_{i=1}^{n} Q_i}{n} \cdot 100, \qquad Q_i = \begin{cases} 1 & if\ Q_i^a = Q_i^r \\ 0 & otherwise. \end{cases} \tag{5}$$

Consequently the IRI, R_i is defined with,

$$R_i(\%) = 100 - R_a(\%). \tag{6}$$

C. Out-of-stocks

Temporary OoSs can occur due to various reasons, some of which can be solved and others not. For example, if a customer purchases all the items of a particular SKU, the item is OoS. This can not be prevented. However, what can for example be adjusted is the replenishment frequency, resulting in a shorter duration of the OoS situation. These unexpected factors are difficult to take into account. A larger problem is 'permanent' OoSs. For example, if the recorded inventory is higher than the actual inventory. The result is that the inventory system 'thinks' that a product is available, while it is not. A replenishment freeze occurs, resulting in a 'permanent' OoS.

Similar to the inventory accuracy, different sources present different OoS percentages: 30-40% [Vermin,], 8-20% [Stelter, 2015], 15-20% [Salmon, 2013] and 16.5% [Salmon, 2016].

In this research, the OoS percentage is measured on the sales floor and can be calculated with equation 7. In which, Q_i^a is the quantity for each SKU on the sales floor.

$$OoSs(\%) = \frac{\sum_{i=1}^{n} N_i}{n} \cdot 100, \qquad N_i = \begin{cases} 1 & if\ Q_i^a = 0 \\ 0 & otherwise. \end{cases} \tag{7}$$

D. RFID-deployments

RFID-deployments can obtain extra information compared to traditional barcode scanners. The RFID-deployments can result in different levels of information regarding the location, accuracy and frequency. In this research, it is assumed that the only difference between the RFID-deployments is the frequency of inventory counts. Each inventory count, the recorded quantity for each SKU is set equal to the actual quantity ($\forall\ i,\ Q_i^r := Q_i^a$). Resulting in a high IRA, directly after an inventory count. The frequency of the inventory counts for each deployment is given in Table I.

TABLE I. FREQUENCY INVENTORY COUNTS

	Count frequency BR	Count frequency SF
Original situation	182 days	182 days
Deployment 1 - handheld readers	7 days	7 days
Deployment 2 - robot reader	1 day	1 day
Deployment 3 - partially overhead/handheld	Continuous	1 day
Deployment 4 - full overhead	Continuous	Continuous

IV. THE SIMULATION MODEL

A. General framework

To compare the impact of the different RFID-deployments, a model is created. The model is based on basic assumptions taken from the literature. The base model is necessary, since every retail store is unique. The constructed base model is shown in Figure 3. The store contains a backroom and a sales floor. The items arrive at the backroom (1), from where the sales floor can be replenished (2). Customers come in and can purchase items from the sales floor (3).

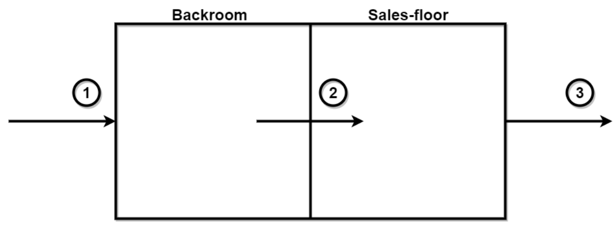

Fig. 3. Schematic view of the retail store modelled

The research focuses on apparel stores, the key difference between apparel stores and retail stores in general are:

- The nature of apparel makes it impossible to do quick visual inventory checks.
- The average quantity and inventory turnover is a lot lower compared to FMCGs.
- Item-level tagging can be used in apparel stores because of the prices of the products and the lack of physical limitations.
- OoSs play a more significant role in apparel retail stores compared to other stores because: a) substitution is limited, b) customers often come to a specific apparel store because of distinct clothes or services, c) customers in apparel stores often buy in low quantities and leave if a product is not available and d) there is more competitive pressure.

The process of the simulation model is shown in Figure 4. R_1 is the in-store replenishment frequency, R_2 is the to-store replenishment frequency and R_3 is the inventory count frequency.

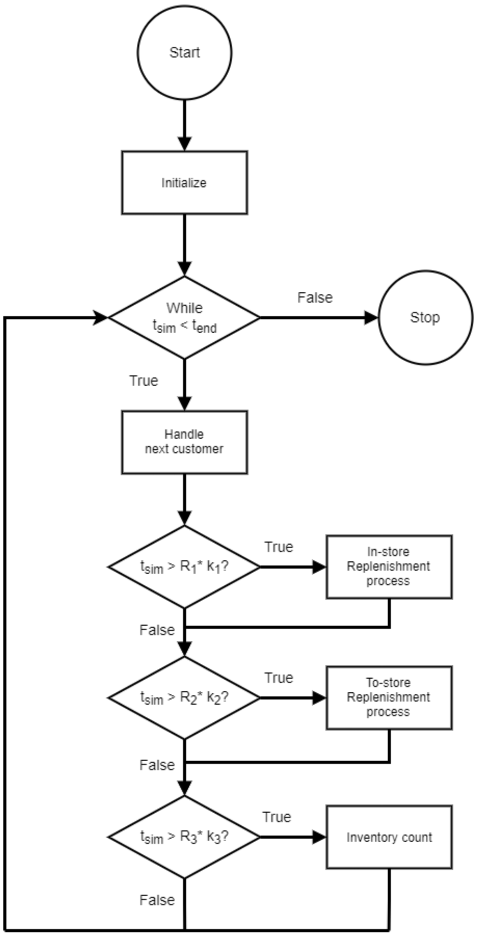

Fig. 4. A flow chart of the store process

The following characteristics are implemented into the model:

TABLE II. CHARACTERISTICS FOR THE APPAREL BASE STORE

What	Value	Explanation
P1: Quantity SKUs	250,6	Number of SKUs and average product quantity per SKU
P2: Replenishment	1w/1d	To-store once a week, in-store once a day
P3: SF/BR ratio	0.5/0.5	Ratio between sales floor and backroom
Inventory turnover	5	The inventory turnover per year
Inventory losses	1.5%/1.5%	Inventory losses on backroom and sales floor
Threshold inventory	10%	Based on average demand and lead time
Lead times	1d/-	To-store 1 day, in-store directly
Customer demand	(0,2)	Lower and uper limit of customer demand
Time in store	10	The time a customer is in the store in minutes

It must be noted that the research focuses on the so called 'Never Out-of-Stock' items, which are always replenished. The model is therefore not suitable for store concepts, which do not replenish a standard inventory frequently.

An example of the graphical output of the model in the original situation is shown in Figure 5. The figure shows that the inventory accuracy deteriorates over time and the percentage of OoSs increases, up till the point that an inventory count is performed.

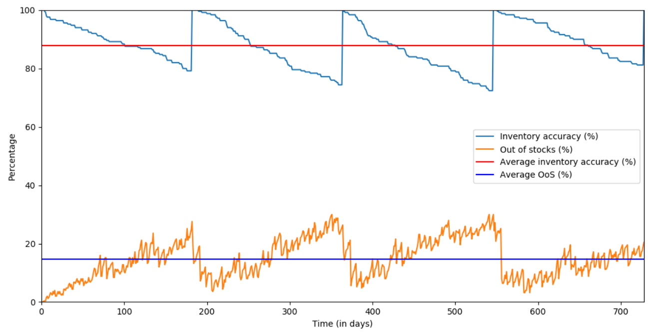

Fig. 5. The inventory accuracy and OoS percentage over time

V. EXPERIMENTS

A. Experimental design

The simulation time is 2 years, the first year is used as initialisation period, the second period is used for data collection. The division between the two periods is halfway the simulation time. Each simulation configuration was performed 100 times. Before running the experiments, the model is calibrated with the following parameters: lead time, inventory turnover factor, delivery errors and the rounding method to compensate errors that are not modelled. The sensitivity analysis for these factors can be found in Appendix A

The following three parameters are adjusted in the experiments to mimic different store types.

1) **Ratios of the sales floor/backroom**
The ratio between the sales floor and backroom can differ significantly per retail store. For example, a shoe store has a small number of products on their sales floor and a discount store almost all. The ratio is varied between 0.25/0.75, 0.5/0.5 and 0.75/0.25.
2) **Average number of products per SKU**
The average number of products per SKU is dependent on the store type. An exclusive store has a low number of items per SKU. A discount store, with limited sizes, could have a high number of items per SKU. The average number of items per SKU is varied between 3,6,12.
3) **Replenishment frequencies**
The replenishment can be divided into the in-store and to-store replenishment frequency. Store replenishments are dependent on various factors. For example, distance to DC, size of the store and type of the store. To-store replenishment is varied between once every three days, weekly and twice a month. In-store replenishment is varied between once every hour and once a day.

B. Results of the experiments

The experiments 1, 2 and 3 give the following results:

TABLE III. RESULTS EXPERIMENT 1 - OOS PERCENTAGES FOR THE SALES FLOOR/BACKROOM RATIOS

	Sales floor/backroom ratio		
	0.25/0.75	0.5/0.5	0.75/0.25
Original situation	17.51%	15.15%	14.90%
Deployment 1	9.30%	7.84%	8.25%
Deployment 2	9.10%	7.65%	7.50%
Deployment 3	9.08%	7.67%	7.44%
Deployment 4	9.05%	7.68%	7.47%

TABLE IV. RESULTS EXPERIMENT 2 - OOS PERCENTAGES FOR THE QUANTITIES PER SKU

	Average quantity per SKU		
	3	6	12
Original situation	12.28%	15.15%	16.04%
Deployment 1	8.62%	7.86%	4.88%
Deployment 2	8.42%	7.71%	4.75%
Deployment 3	8.43%	7.67%	4.69%
Deployment 4	8.39%	7.65%	4.62%

TABLE V. RESULTS EXPERIMENT 3 - OOS PERCENTAGES FOR THE REPLENISHMENT FREQUENCIES

	To-store: 3 days In-store: 1 hour	To-store: 3 days In-store: 1 day	To-store: 7 days In-store: 1 hour	To-store: 7 days In-store: 1 day	To-store: 14 days In-store: 1 hour	To-store: 14 days In-store: 1 day
Original situation	11.54%	13.31%	13.69%	15.14%	16.96%	18.28%
Deployment 1	3.95%	5.72%	6.10%	7.86%	9.57%	11.29%
Deployment 2	3.86%	5.63%	6.00%	7.70%	9.46%	11.12%
Deployment 3	3.85%	5.62%	5.95%	7.65%	9.43%	10.08%
Deployment 4	3.81%	5.58%	5.92%	7.65%	9.37%	11.03%

Analysis of the results

For each store configuration, the OoS percentage in the original situation is different. To analyse the benefits of the RFID-deployments for a specific store configuration, the deployments are compared to their original situation. The comparison to the original situation gives the following results for experiment 1, 2 and 3:

TABLE VI. EXPERIMENT 1 - RELATIVE IMPROVEMENT: RATIO SALES FLOOR/BACKROOM

	Sales floor/backroom ratio		
	0.25/0.75	0.50/0.50	0.75/0.25
Deployment 1	46.89%	48.27%	48.82%
Deployment 2	48.01%	49.51%	49.63%
Deployment 3	48.12%	49.40%	50.04%
Deployment 4	48.30%	49.31%	49.86%

TABLE VII. EXPERIMENT 2 - RELATIVE IMPROVEMENT: QUANTITIES PER SKU

	Quantity per SKU		
	3	6	12
Deployment 1	29.75%	48.14%	69.58%
Deployment 2	31.40%	49.10%	70.39%
Deployment 3	31.32%	49.36%	70.73%
Deployment 4	31.61%	49.53%	71.21%

TABLE VIII. EXPERIMENT 3 - RELATIVE IMPROVEMENT: REPLENISHMENT FREQUENCIES

	To-store: 3 days In-store: 1 hour	To-store: 3 days In-store: 1 day	To-store: 7 days In-store: 1 hour	To-store: 7 days In-store: 1 day	To-store: 14 days In-store: 1 hour	To-store: 14 days In-store: 1 day
Deployment 1	65.79%	57.06%	55.41%	48.05%	43.55%	38.24%
Deployment 2	66.58%	57.73%	56.18%	49.11%	44.22%	39.17%
Deployment 3	66.66%	57.79%	56.52%	49.46%	44.42%	39.40%
Deployment 4	66.97%	58.10%	56.79%	49.47%	44.74%	39.69%

It is key for retailers to find the balance between an acceptable number of OoSs and overstocks. Doubling the inventory to reduce the OoS percentage is therefore not a viable solution. To test if the solutions are viable, is is assumed that item availability can be directly linked to the sales. The percentage increase in sales is compared to the percentage increase in inventory with the relative improvement factor, f. If the increase in sales is higher than the increase in inventory ($f > 1$), the deployment is viable. If the sales decrease ($f < 1$), the deployment is not viable. If both increase, but the increase in inventory is larger than the increase in sales, it is unable to determine if the deployment viable without a more comprehensive economical analysis ($0 < f < 1$).

The relative improvement factor for experiment 1, 2 and 3 is given below:

TABLE IX. EXPERIMENT 1 - RELATIVE IMPROVEMENT FACTOR: SALES FLOOR/BACKROOM RATIO

	Sales floor/backroom ratio		
	0.25/0.75	0.50/0.50	0.75/0.25
Deployment 1	2.28	1.66	1.44
Deployment 2	2.31	1.69	1.43
Deployment 3	2.39	1.60	1.37
Deployment 4	2.33	1.89	1.44

TABLE X. EXPERIMENT 2 - RELATIVE IMPROVEMENT FACTOR: AVERAGE QUANTITY PER SKU

	Quantity per SKU		
	3	6	12
Deployment 1	1.80	1.72	4.37
Deployment 2	1.60	1.74	4.71
Deployment 3	1.49	1.65	4.35
Deployment 4	1.43	1.71	3.86

TABLE XI. EXPERIMENT 3 - RELATIVE IMPROVEMENT FACTOR: REPLENISHMENT FREQUENCY

	To-store: 3 days In-store: 1 hour	To-store: 3 days In-store: 1 day	To-store: 7 days In-store: 1 hour	To-store: 7 days In-store: 1 day	To-store: 14 days In-store: 1 hour	To-store: 14 days In-store: 1 day
Deployment 1	1.75	1.64	1.63	1.76	1.93	1.80
Deployment 2	1.75	1.66	1.62	1.75	1.80	1.72
Deployment 3	1.77	1.65	1.55	1.68	1.89	1.84
Deployment 4	1.70	1.67	1.53	1.64	1.75	1.68

VI. CONCLUSION

A. Conclusion

The goal of the study was to compare the different RFID-deployments for various retail store configurations. Following the results of the experiments, it can be concluded that every RFID-deployment for each store configuration significantly reduces the percentage of OoSs and is viable. The relative differences between RFID-deployment 1 up to 4 are extremely small. However, there are significant differences between several store types. The results for different sales floor/backroom ratios are more or less similar and match the average reduction. In experiment 2 and 3, significant differences can be seen. RFID shows the most benefits for retail stores with higher quantities per SKU and stores that are replenished more frequently. Furthermore, the OoS percentages are dependent on other variables, which is measured with a sensitivity analysis. The dependency on other variables is given in Appendix A

B. Discussion

The simulation model is built to get an understanding of the benefits of different RFID-deployments regarding the reduction of OoS. Simplifications and assumptions had to be made in order to keep the model generic and be able to compare different store types. The model has the following limitations: 1) The parameters of the experiments are chosen arbitrary, in reality each retail store is unique and parameters can have different values. 2) The inventory representation is simplified compared to a real inventory, as is the demand. 3) The differences between the RFID-deployments are limited to the frequency of the inventory counts. 4) Several small processes are left out.

Follow-up research is advised in the following three fields: 1) Extent the model with real data or an improved implementation of RFID. 2) Extent the cost-benefit analysis to get a complete overview of a specific RFID-deployment for a store type. 3) Run a pilot project, to get test the RFID-deployment in reality for a particular store.

Appendix A
Sensitivity analysis

The variables can differ for each apparel store. A sensitivity analysis is performed to test the influence of different variables. Figures 6 to 12 show the results of the sensitivity analysis.

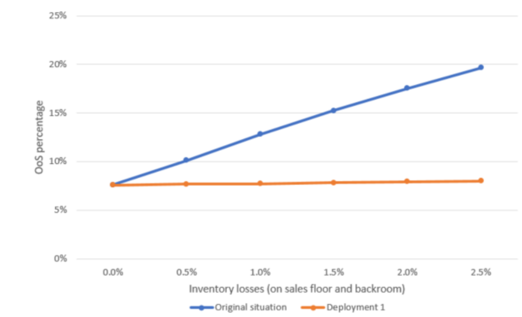

Fig. 6. Sensitivity analysis - Inventory losses

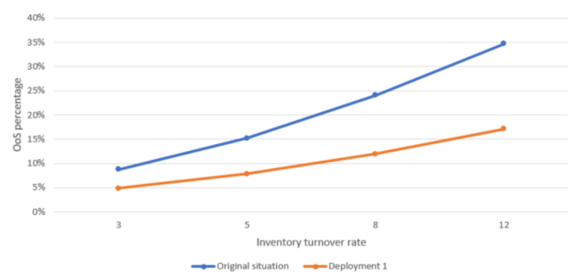

Fig. 7. Sensitivity analysis - Inventory turnover rate

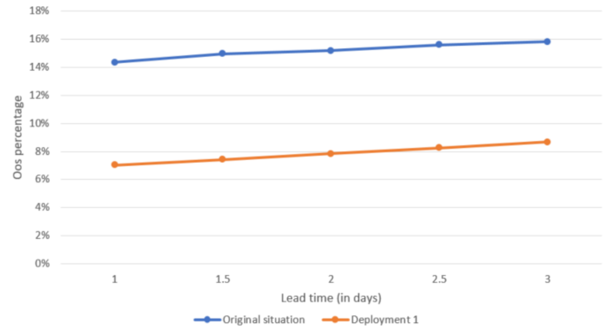

Fig. 8. Sensitivity analysis - Lead time

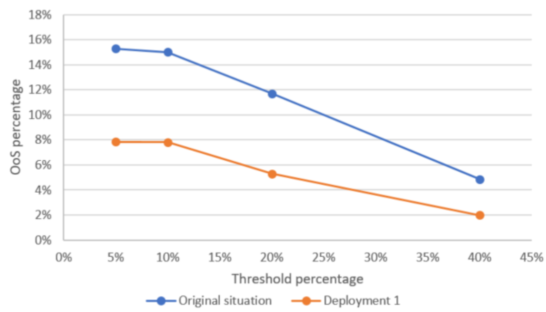

Fig. 9. Sensitivity analysis - Threshold percentage

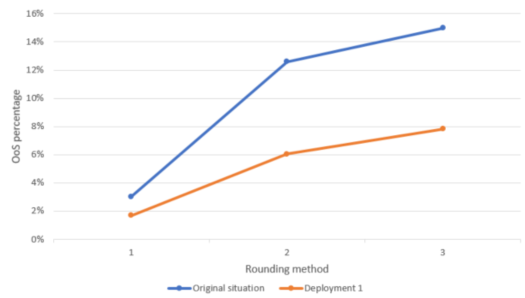

Fig. 10. Sensitivity analysis - Rounding

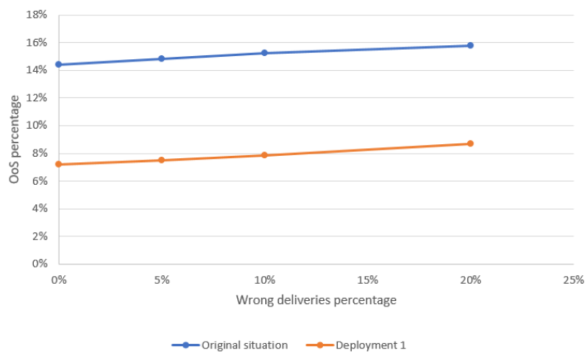

Fig. 11. Sensitivity analysis - Delivery Errors

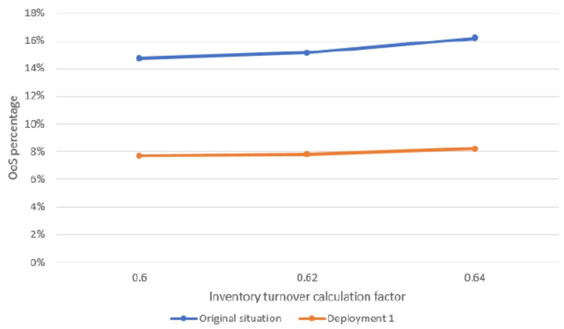

Fig. 12. Sensitivity analysis - Inventory turnover calculation factor

Appendix B
Average inventory for each experiment

The average inventory for experiment 1, 2 and 3 to calculate the relative improvement factor.

TABLE XII. Experiment 1 - average inventory

	Sales floor - backroom ratio		
	0.25/0.75	0.50/0.50	0.75/0.25
Original situation	816	809	802
Deployment 1	852	851	849
Deployment 2	852	852	851
Deployment 3	851	854	853
Deployment 4	852	847	850

TABLE XIII. Experiment 2 - average inventory

	Average quantity per SKU		
	3	6	12
Original situation	470	809	1614
Deployment 1	481	850	1663
Deployment 2	483	850	1660
Deployment 3	484	853	1664
Deployment 4	485	851	1671

TABLE XIV. Experiment 3 - average inventory

	To-store: 3 days In-store: 1 hour	To-store: 3 days In-store: 1 day	To-store: 7 days In-store: 1 hour	To-store: 7 days In-store: 1 day	To-store: 14 days In-store: 1 hour	To-store: 14 days In-store: 1 day
Original situation	825	823	805	810	786	786
Deployment 1	866	867	848	850	822	823
Deployment 2	866	868	849	851	825	826
Deployment 3	866	868	851	852	823	823
Deployment 4	867	868	852	854	827	827

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Appendix B

The Appendix

B-1 Information about Mieloo & Alexander

The following information is directly cited from their website [M&A,]:

"Mieloo & Alexander Business Integrators is specialised in delivering "technology enabled supply chain improvement". We successfully design, plan and implement technology solutions and transform your organisation to achieve operational excellence and sustainable competitive advantage.

As supply chain and logistics consultants we support our clients with their strategy, (re-) design of processes, organisation and (ERP) systems, and with planning and managing the transformation project.

And as AutoID integrators (with a focus on UHF Radio Frequency IDentification (RFID) technology), we design, build and implement custom solutions to realise the benefits of (AutoID) technology and to improve and innovate the (internal) business processes of our clients. We also offer branded, modular/integrated solutions for Horticulture (ScanGreen) and Returnable Asset Tracking (RTEye), and provide maintenance and support of the solutions we deliver with a dedicated support team.

We combine our business consulting expertise, skills and experience with in-depth knowledge of your business and technology, and with a proven capability to manage large scale, business or technology driven transformation programs.

We manage risk and take responsibility for results; are clear, systematic and determined, deliver outstanding client service, measurable results and satisfied customers. Abiding to our core values has resulted in a customer base of multi-national corporations with (European) Head Quarters or subsidiaries in the Benelux, Germany and the United Kingdom. We are active in the Agri- and Horticulture, Retail and Consumer Goods, High Tech, Automotive, Trade/Logistics/Postal, Industry and Defence and Health/Care".

B-2 Examples of RFID-readers

Figure B-1: RFID handheld reader - source: Zebra

Figure B-2: RFID handheld reader - source: J&J Cooperated

Figure B-3: RFID robot reader - source: Pal robotics

Figure B-4: RFID robot reader - source: RFspot

Figure B-5: RFID overhead reader - source: Mojix

Figure B-6: RFID overhead reader - source: Expo 21xx

B-3 Business case

The following aspects should be taken into account to calculate a more complete cost-benefit analysis to determine if a return on investment can be made for a specific RFID-deployment.

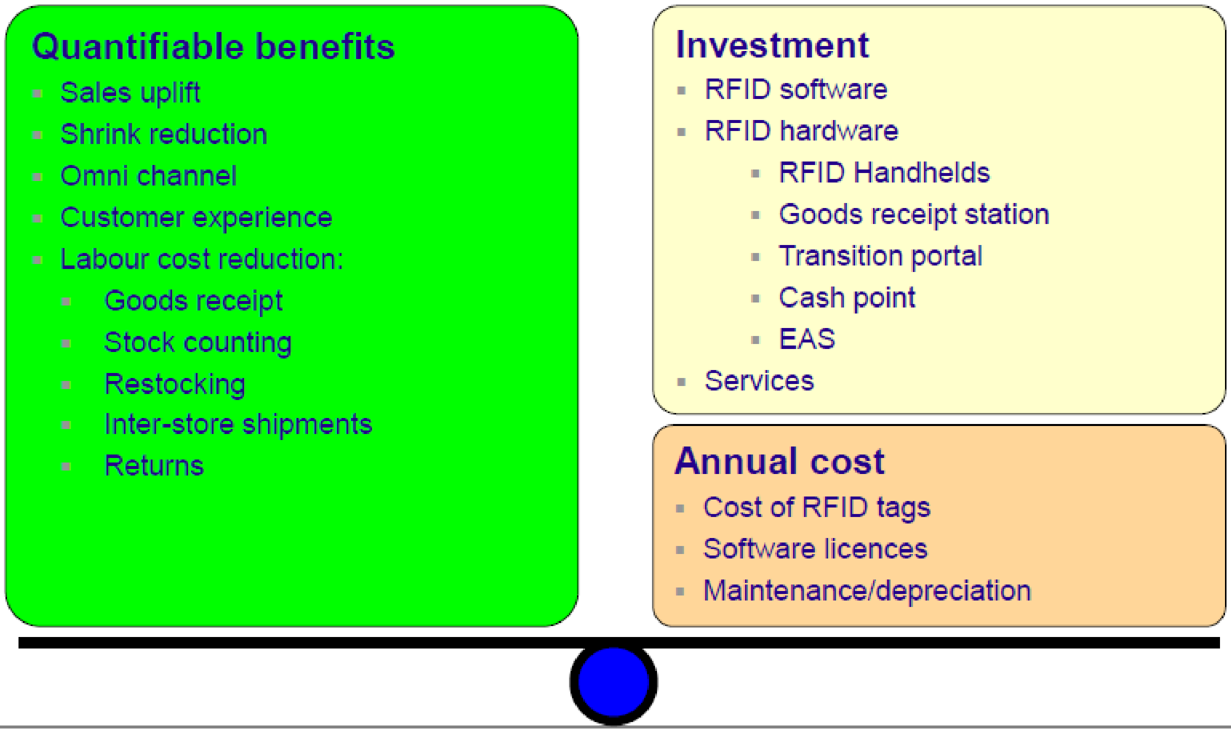

Figure B-7: RFID business case - source: Mieloo & Alexander

B-4 Average inventory per experiment

The average inventory for each situation in the three experiments.

Table B-1: Experiment 1 - average inventory

	Sales floor - backroom ratio		
	0.25/0.75	0.50/0.50	0.75/0.25
Original situation	816	809	802
Deployment 1	852	851	849
Deployment 2	852	852	851
Deployment 3	851	854	853
Deployment 4	852	847	850

Table B-2: Experiment 2 - average inventory

	Average quantity per SKU		
	3	6	12
Original situation	470	809	1614
Deployment 1	481	850	1663
Deployment 2	483	850	1660
Deployment 3	484	853	1664
Deployment 4	485	851	1671

Table B-3: Experiment 3 - average inventory

	To-store: 3 days In-store: 1 hour	To-store: 3 days In-store: 1 day	To-store: 7 days In-store: 1 hour	To-store: 7 days In-store: 1 day	To-store: 14 days In-store: 1 hour	To-store: 14 days In-store: 1 day
Original situation	825	823	805	810	786	786
Deployment 1	866	867	848	850	822	823
Deployment 2	866	868	849	851	825	826
Deployment 3	866	868	851	852	823	823
Deployment 4	867	868	852	854	827	827

B-5 Experiment 2 with an equal total number of products

All simulation runs for experiment 2 are performed with 250 Stock Keeping Units (SKUs), where only the average quantity per SKU was adjusted. This resulted in large differences in the average inventory. The average inventory with products quantities of 3 was around 480 and for average product quantities of 12 around 1660.

Since the inventory turnover is constant, more products result in more customers. To exclude this effect, another experiment is performed where the initial inventory is equal. The initial inventory is the base model is $250 \cdot 6 = 1500$. If the average product quantity is 3, it results in 500 SKUs and for 12 in 125 SKUs.

Rerunning experiment 2 gives the following results:

Table B-4: Experiment 2 with an equal total inventory: OoS percentages

	Average quantity per SKU		
	500, 3	250, 6	125, 12
Original situation	12.32%	15.15%	15.82%
Deployment 1	8.47%	7.86%	4.87%
Deployment 2	8.38%	7.71%	4.72%
Deployment 3	8.37%	7.67%	4.72%
Deployment 4	8.34%	7.65%	4.77%

Table B-5: Experiment 2 with an equal total inventory: Average inventory

	Average quantity per SKU		
	500, 3	250, 6	125, 12
Original situation	937	809	812
Deployment 1	968	850	830
Deployment 2	967	850	832
Deployment 3	965	853	831
Deployment 4	967	851	828

The conclusion is that the number of SKUs does not significantly influence the OoS percentages for experiment 2. This conclusion is in line with the test if the quantity of the number of SKUs influences the percentage of OoS for the original situation and deployment 1, show in Table B-6.

Table B-6: Sensitivity analysis - number of SKUs

	Number of different SKUs		
	125	250	500
Original situation	15.34%	15.10%	15.13%
Deployment 1	7.93%	7.84%	7.81%

B-6 Sensitivity analysis of the calibration

In a calibration, values can be adjusted according to literature, measurements, expert views or other references. The variables for the base model are assumed and can be different for each retail store. Therefore, there is no standard reference and different values are found in the literature. For example, for a particular retail store the lead time could be 1 day and for another 4 days. A sensitivity analysis on the influences on these calibration variables is presented in this section. It must be noted that the variables are adjusted from the base model after the fifth calibration. Effects could therefore slightly differ in the original model before the calibration. A sensitivity analysis for the lead time is already performed in Chapter 8. The sensitivity analysis analyses the inventory turnover calculation factor, the delivery errors and the rounding method.

The following variables are used in the base model:

Table B-7: The variables used in the base model after the calibration

t_{lead}	f	E_d	M_R
2 days	0.62	10%	3

B-6-1 Inventory turnover calculation factor

The sensitivity analysis for the inventory turnover calculation factor gives the following results:

Table B-8: Sensitivity analysis - inventory turnover calculation factor

	Inventory turnover factor		
	0.60	0.62	0.64
Original situation	14.74%	15.15%	16.18%
Deployment 1	7.70%	7.81%	8.21%

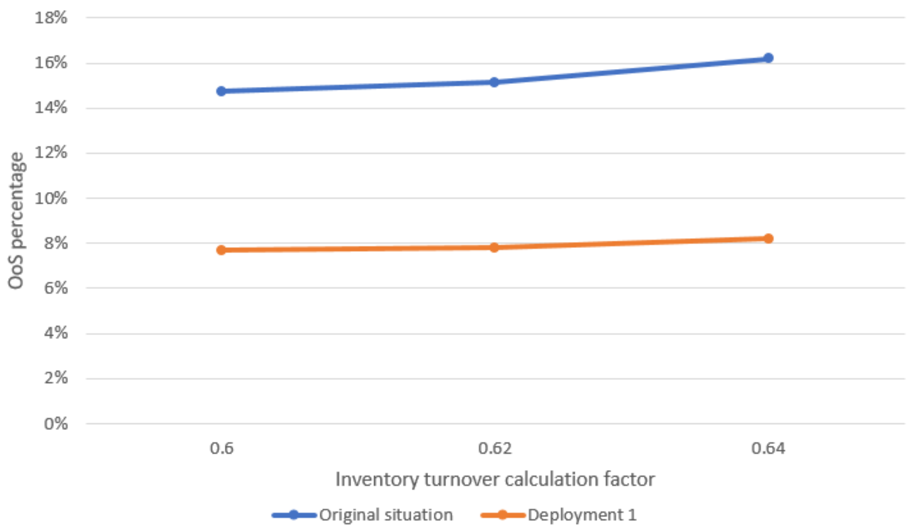

Figure B-8: Dependence of OoSs on the inventory turnover calculation factor

B-6-2 Delivery errors

The sensitivity analysis for the delivery errors gives the following results:

Table B-9: Sensitivity analysis - delivery errors

	Wrong deliveries			
	0%	5%	10%	20%
Original situation	14.41%	14.81%	15.23%	15.81%
Deployment 1	7.17%	7.48%	7.84%	8.69%

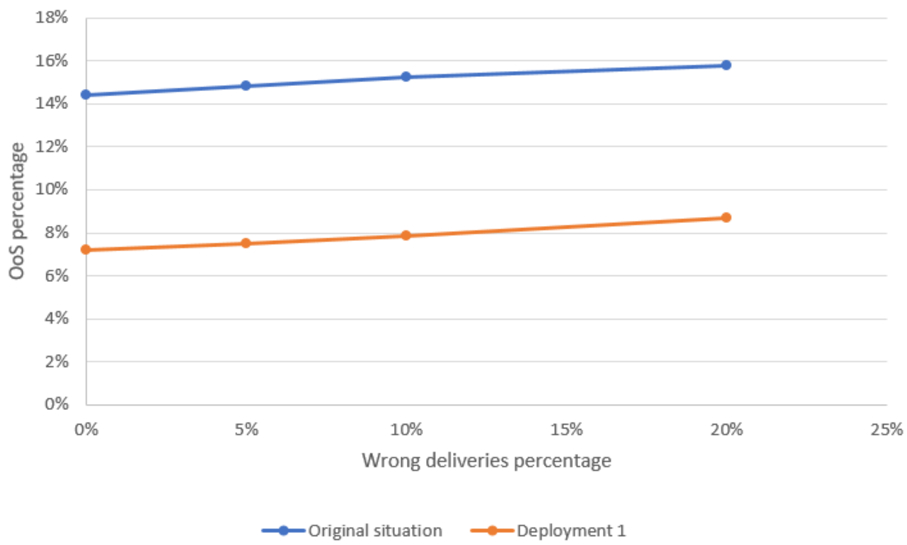

Figure B-9: Dependence of OoSs on delivery errors

B-6-3 Rounding method

The rounding method is used to determine the threshold value for the replenishment. Rounding method 1 is rounding up, rounding method 2 is rounding regularly and rounding method 3 is rounding down.

The sensitivity analysis for the rounding method gives the following results:

Table B-10: Sensitivity analysis - rounding method

	Rounding method		
	1	2	3
Original situation	3.02%	12.60%	14.97%
Deployment 1	1.70%	6.04%	7.82%

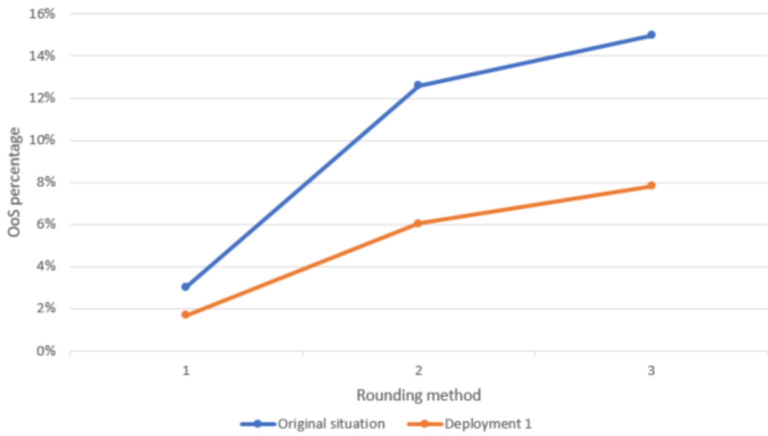

Figure B-10: Dependence of OoSs on the rounding method

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